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**Heterogeneity and skill in the retail EUR/USD FX market
Investigating the impact of uncertainty and behavioural biases of trader skills**

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HETEROGENEITY AND SKILL IN THE RETAIL EUR/USD FX MARKET: INVESTIGATING THE IMPACT OF UNCERTAINTY AND BEHAVIOURAL BIASES ON TRADER SKILLS



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Abstract

One of the issues that has been debated in the literature is market heterogeneity. Traditional financial models adopt a popular assumption that markets are efficient and that participants act rationally such that their actions are homogeneous. Nevertheless, behavioural finance literature provides significant evidence of behavioural patterns and biases which render the assumption of homogeneity too simplistic and idealistic. Heterogeneity in financial markets can be defined as significant diversity in expectations of asset prices.

I examine two aspects of heterogeneity in this thesis: trader's performance and trader's expectations. I also investigate whether traders possess genuine trading skills and how market volatility as well as a trader's personal behavioural biases affect their skills. Using a dataset of more than twenty-one thousand retail FX traders on the EUR/USD market I find significant evidence of heterogeneity in performance and expectations, which persists throughout their trading career. I show that while around 68% of traders have the ability to correctly predict future price changes more than half of the time, only around 22.8% have the ability to generate overall positive returns. In addition, around 27% of traders have the ability to favourably adjust their position size based on the magnitude of the change in market prices. Moreover, I find that volatility has a detrimental impact on performance. Nevertheless, as this uncertainty becomes seasoned, individuals learn to understand it and adjust for it in their trading decisions. Finally, I find that skilled traders are herd initiators such that they are closely watched and copied by others. I also show that skilled traders exhibit the disposition effect, whereby they are more likely to realise small gains and hold on to large losses.

In addition, skilled traders are also sensation seekers, indicating that they tend to use leverage to exploit price change; however, they tend to avoid extreme levels of leverage which can be detrimental to the performance and reputation. Skilled traders are more likely to be inconsistent in the amount of leverage and margin they use, which is explained by their ability to adjust their leverage ratio depending on the state of the market and their confidence in their trading decision.

This thesis contributes to the literature on the micro dynamics of retail FX markets. My findings highlight the importance of understanding trader behaviour which provides insight into the decision-making process of individual traders and how these decisions are affected by endogenous behavioural factors as well as external market factors.

Declaration

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Number of words: 66,937

Name: DEMETRIOS ZAMBOGLOU

A handwritten signature in dark ink, appearing to be 'Demetrios Zamboglou', written in a cursive style.

Signed Date: May 27, 2018

Table of Contents

SECTION 1. INTRODUCTION.....	1
SECTION 2. LITERATURE REVIEW	10
2.1 HETEROGENEOUS TRADERS.....	10
2.1.1 Asymmetric Information as a Source of Heterogeneity.....	10
2.1.2 Heterogeneity in Trader Behaviour.....	13
2.1.3 Market Impact on Heterogeneity.....	15
2.1.4 Heterogeneity in Forecasts and Trading Strategies.....	17
2.1.5 Heterogeneity in Risk Tolerance.....	20
2.1.6 Empirical Literature on Heterogeneity.....	22
2.2 TRADING SKILLS	37
2.2.1 Identifying Skilled Traders	37
2.2.2 Skill Among Retail FX Traders.....	40
2.2.3 Forecasting Power of Trading Strategies.....	43
2.2.4 Institutional Forecasters and Traders	49
2.2.5 Evidence on Futures Traders	50
2.2.6 Evidence on Stock Traders.....	53
2.2.7 A Note on Skill v.s. Luck.....	56
2.3 MARKET VOLATILITY	58
2.3.1 Market Participation and Volatility.....	58
2.3.2 Trader Expectations and Volatility	59
2.3.3 Volume and Volatility	64
2.3.4 News and Volatility	67
2.3.5 Impact of Volatility on Trader Performance.....	69

2.4 THE EFFECT OF BEHAVIOURAL BIASES ON PERFORMANCE AND SKILL	73
2.4.1 Herd Initiations.....	73
2.4.2 Disposition Effect.....	82
2.4.3 Sensation-Seeking.....	94
2.4.4 Inconsistent Behaviour	100
2.4.5 Information Advantage.....	108
2.5 RESEARCH QUESTIONS.....	124
SECTION 3. HYPOTHESES, DATA AND ANALYTICS	128
3.1 HYPOTHESES SECTION	128
3.1.1 Hypothesis 1: Measuring heterogeneity among traders	128
3.1.2 Hypothesis 2: Identifying genuine trading skills	129
3.1.3 Hypothesis 3: The impact of volatility on trading skills	131
3.1.4 Hypothesis 4: The impact of behavioural biases on trading skills....	133
3.2 DATA AND METHODOLOGY	134
3.2.1 Retail Trading Operations.....	134
3.2.2 Data. Descriptive Statistics	138
3.2.3 Methodology	140
3.3 RESULTS AND DISCUSSIONS	160
3.3.1 Testing for Heterogeneity	160
3.3.2 Identifying Skilled Traders	181
3.3.3 Examining the Impact of Market Volatility on Skill	184
3.3.4 The Impact of Behavioural Biases on Trader Skill	189

SECTION 4. CONCLUSION AND FUTURE WORK	196
4.1 CONCLUSION.....	196
4.2 CONTRIBUTION	199
4.3 LIMITATIONS OF THIS THESIS	201
4.4 FUTURE WORK.....	202

List of Tables

TABLE 1.1: DESCRIPTIVE STATISTICS OF TRADERS ON THE ANONYMOUS PLATFORM.....	246
TABLE 1.2: CORRELATION MATRIX OF VARIABLES.....	247
TABLE 2.1.1.1: HETEROGENEITY IN PERFORMANCE – SUCCESS RATE - LOGISTIC MODEL USING TRANSACTION DATA.....	248
TABLE 2.1.1.2: HETEROGENEITY IN PERFORMANCE – RETURN ON INVESTMENT - LOGISTIC MODEL USING TRANSACTION DATA.	249
TABLE 2.1.2.1: HETEROGENEITY IN PERFORMANCE – SUCCESS RATE - LINEAR MODEL USING DAILY AGGREGATED DATA.	250
TABLE 2.1.2.2: HETEROGENEITY IN PERFORMANCE – RETURN ON INVESTMENT - LINEAR MODEL USING DAILY AGGREGATED DATA.	251
TABLE 2.1.3.1: HETEROGENEITY IN PERFORMANCE – SUCCESS RATE - LOGISTIC MODEL USING DAILY AGGREGATED DATA.	252
TABLE 2.1.3.2: HETEROGENEITY IN PERFORMANCE – RETURN ON INVESTMENT - LOGISTIC MODEL USING DAILY AGGREGATED DATA.	253
TABLE 2.2: HETEROGENEITY IN EXPECTATIONS.....	253
TABLE 3.1: IMPACT OF VOLATILITY ON SUCCESS RATE - LOGISTIC MODEL USING TRANSACTION DATA.....	255
TABLE 3.2: IMPACT OF VOLATILITY ON ROI.	256

TABLE 3.3: IMPACT OF VOLATILITY ON SUCCESS RATE - LINEAR MODEL USING DAILY AGGREGATED DATA.	257
TABLE 4: IMPACT OF BEHAVIOURAL BIASES ON SKILLS	258

LIST OF TABLES IN APPENDIX

TABLE A.1: HETEROGENEITY IN PERFORMANCE – SUCCESS RATE - LOGISTIC MODEL USING TRANSACTION DATA INCLUDING CAREER ROI.	259
TABLE A.2: HETEROGENEITY IN PERFORMANCE – RETURN ON INVESTMENT - LOGISTIC MODEL USING TRANSACTION DATA INCLUDING CAREER SUCCESS.	260
TABLE A.3: HETEROGENEITY IN PERFORMANCE – SUCCESS RATE - LOGISTIC MODEL USING TRANSACTION DATA – 90% WINSORISATION.	261
TABLE A.4: HETEROGENEITY IN PERFORMANCE – RETURN ON INVESTMENT - LOGISTIC MODEL USING TRANSACTION DATA – 90% WINSORISATION.	262
TABLE A.5: HETEROGENEITY IN PERFORMANCE – SUCCESS RATE - LINEAR MODEL USING DAILY AGGREGATED DATA – 90% WINSORISATION.	263
TABLE A.6: HETEROGENEITY IN PERFORMANCE – RETURN ON INVESTMENT - LINEAR MODEL USING DAILY AGGREGATED DATA – 90% WINSORISATION.....	264
TABLE A.7: HETEROGENEITY IN PERFORMANCE – SUCCESS RATE - LOGISTIC MODEL USING DAILY AGGREGATED DATA – 90% WINSORISATION.	265
TABLE A.8: HETEROGENEITY IN PERFORMANCE – RETURN ON INVESTMENT - LOGISTIC MODEL USING DAILY AGGREGATED DATA – 90% WINSORISATION.....	266

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Last but not least, I dedicate this PhD to my father.

"Dreams are not negotiable" — Paulo Coelho

Section 1. Introduction

Traditional financial theory is based on the notion that traders act rationally. This means that all market participants have the same expectations of asset returns, and their sole objective is to maximise risk-adjusted returns. Moreover, these individuals have access to the same publicly disclosed set of market information, and asset prices reflect all information such that participants are unable to achieve above average risk-adjusted returns. Under this scenario, financial markets are considered to be highly efficient, and the performance of participants is homogeneous.

The assumption of homogeneity is at the core of many popular financial frameworks, such as modern portfolio theory and the capital asset pricing model (Markowitz, 1952a; Treynor, 1961; Sharpe, 1964; Lintner, 1965).

Nevertheless, many academics have argued that homogeneity is a very strong assumption, which does not hold, especially in the presence of speculative markets (Frechette and Weaver, 2001). This is because individuals exhibit different performance outcomes, and in many cases irrational behaviour depending on the state of the market. Moreover, individuals may interpret the same piece of information differently due to their personal biases, thus leading to different conclusions about financial markets. As such, there has been a growing branch of literature, which advocates that financial markets are in fact heterogeneous and that one should take into account this phenomenon when examining asset returns as well as the performance of investors (Abbey and Doukas, 2015; Hayley and Marsh, 2016).

Little research has been conducted to investigate the heterogeneity of traders in retail FX markets, mainly due to the lack of access to transaction level data. Nevertheless, two recent papers by Abbey and Doukas (2015) and Hayley and Marsh (2016) have examined this phenomenon, and have found significant evidence of heterogeneity in performance among retail FX traders. However, these studies have focused on the heterogeneity in performance using daily aggregated data which does not allow them to control for trade specific characteristics (Hayley and Marsh, 2016) or using a factor based model (Abbey and Doukas, 2015). Moreover, the previous studies did not investigate heterogeneity in trader expectations which allows us to examine the dispersion of trader forecasts around the daily consensus.

The dataset used in this thesis contains transaction level information, which allows me to investigate heterogeneity at the transaction level, as well as heterogeneity in trader expectations. Specifically, I aim to answer the following research question: Is there significant heterogeneity in performance and expectations among retail traders in the EUR/USD foreign exchange market?

Using a detailed transaction level dataset, I adopt the methods used in the literature to investigate heterogeneity in performance (Hayley and Marsh, 2016), and heterogeneity in expectations (Ito, 1990), among 21,300 retail FX traders in the EUR/USD market. Retail FX traders typically open positions for short periods of time (which can range from few minutes to several days), hence given the short-lived nature of their trades these traders do not follow a buy and hold strategy. Moreover, retail FX traders are usually less skilled and have access to less sophisticated tools and data compared to institutional traders. After

controlling for trader characteristics, I find significant evidence of heterogeneity in performance among traders and in expectations of future EUR/USD spot prices¹. Moreover, I find that persistence in heterogeneity increases as traders move forward in their trading career.

The evidence presented on heterogeneity among these retail traders raises the question of whether some individuals possess genuine skill. In other words, “knowing that the population is heterogeneous with some traders being skilled and others unskilled” (Hayley and Marsh, 2016).

One of the most intriguing puzzles in finance is to identify traders who possess genuine trading skills. While skill can be broadly defined as an individual’s ability to add value to a certain investment, testing for such ability is not a simple task. The main obstacle is selecting appropriate statistics to measure skill.

In other words, do some traders have the ability to consistently (more than half of the time) and correctly predict future price changes in the foreign exchange market? This brings us to the second research question: Do (some) retail FX traders possess genuine trading skills, such that they are able to consistently predict future price movements (in a market that has often been described as following a random walk), add value in absolute terms and adjust the size of their position based on their confidence in their forecast?

Many academics have used the percentage of winning trades or success rate (SR) as an indication of a trader’s ability to consistently predict future price

¹This thesis does not investigate market efficiency per se, however there is significant evidence showing that foreign exchange markets including EUR/USD can be characterised fairly close to random walk (Pukthuanthong-Le and Thomas, 2008).

changes. This measure indicates whether a trader possesses superior skill, which may take the form of private information or advanced modelling techniques; however, it does not capture a trader's ability to add value in absolute terms. To remedy this, others have proposed using the return on investment (ROI) in order to measure the value added by the trader over time. A third performance measure that has been applied in the literature is the big hit ability (BHA), which measures a trader's ability to adjust the size of his position contingent on his confidence in his expectation about future market prices (Hartzmark, 1991).

In this analysis, I use all three of these measures in order to obtain a complete assessment of currency traders' skills. In general, I find that although around 68% of retail FX traders can consistently predict future price changes, only 22.8% of individuals possess the ability to generate positive overall returns as indicated by their ROI. In addition, the mean ROI across all traders is -28.8%, which means that retail FX traders on average lose money. Finally, with respect to BHA, I find that traders exhibit negative BHA on average, with only 27% of traders showing positive BHA.

One important factor that affects the skills of traders is market volatility (Olson, 2004; Qi and Wu, 2006). Hence, I examine how heightened market volatility impacts the skills of retail FX traders in order to answer the third research question: How does heightened market volatility affect the skills of individual FX traders?

I investigate how market volatility impacts traders' predictive ability as well as their ability to generate positive returns. To do so, I estimate a series of models where I examine the effect of volatility on the day a position was opened in

addition to the lagged volatility of the previous 10 trading days² (short-term trading horizon) on the success rate (i.e. predictive ability) and the ROI of the trader for each trading day. I also use a binary volatility variable to capture the effects of high market uncertainty on trader skill and performance.

In general, the results show that traders are unable to correctly integrate recent market uncertainty in their predictions; however, as this information becomes seasoned for several days they are better able to use it to gauge future price movements. Furthermore, I find that high market uncertainty has a negative impact on a trader's ability to predict future price movements. This may be due to lack of good quality information during times of market turbulence in addition to behavioural biases such as fear, which drives traders to make decision-based on sentiment rather than sound economic analysis.

With respect to the impact of volatility on the traders' returns (ROI), the models have a poor fit and most parameters are statistically insignificant. Nevertheless, there is some evidence that high market volatility negatively affects a trader's ability to generate positive returns. In general, the results show that market volatility is detrimental to both a trader's ability to correctly predict future price changes, as well as their ability to generate positive economic returns.

Another element that also plays an important factor in shaping a trader's skills is his behaviour. This brings forth the final research question of my thesis: How do behavioural biases impact the skills of retail FX traders?

² I conduct autoregressive analysis on the lagged volatility parameters and find significant coefficients only up to 10 lags. As such, my models include volatility lags of 10 periods.

I examine the relationship between five behavioural biases, namely herd initiations, the disposition effect, sensation seeking, inconsistent behaviour, and information advantage and the skills of traders, which are captured by three measures: Success Ratio (SR), Return on Investment (ROI), and Big Hit Ability (BHA). This analysis allows us to better understand how these behavioural biases affect the decision-making process of traders and how they impact skill.

In general, I find that traders who possess all three skills are herd initiators, meaning that they are closely watched and copied by others. In addition, these traders also exhibit the disposition effect such that they are more likely to realise small gains and hold on to large losses. This may be interpreted as a beckoning mechanism such that these traders realise many small gains to signal to others that they possess superior trading skills. Skilled traders are also sensation seekers, meaning that they tend to use leverage to exploit price changes; however, they tend to avoid extreme leverage levels, which can be detrimental to their performance. Moreover, skilled traders tend to be inconsistent in the amount of leverage and margin they use. This may be interpreted as the skilled traders' ability to adjust the amount of leverage used depending on the state of the market and their confidence in their decisions. Finally, I find that traders who have high SR tend to execute trades that quickly move into-the-money, while those with low SR tend to have longer trade durations before the trade covers the spread cost. This analysis allows us to better understand the behavioural biases of skilled and unskilled traders and how these biases play a role in shaping the decision-making process and skill set of a trader.

This thesis contributes to the literature on the performance and behaviour of retail traders in the foreign exchange market. First, my findings show significant heterogeneity among retail traders in the EUR/USD market. This evidence challenges traditional financial theory, which states that market participants have homogeneous expectations for asset returns and risks. On the contrary, I show that heterogeneity is a constant and persistent characteristic of the retail EUR/USD market. As such, traditional FX pricing models may be improved by incorporating the microstructural dynamics of the FX market, which can be explained by the diversity and magnitude in expectations on either side of the market. My second contribution sheds light on the skills of retail FX traders. In particular, my findings show that while many traders possess the ability to correctly forecast the direction of future price movements, very few have the ability to add positive returns in absolute terms. This highlights the importance of investigating both the ability to be on the correct side of the market and the ability to generate positive returns, which would allow us to distinguish between those who are genuinely skilled and those who are simply lucky. Moreover, it is crucial for retail traders to be aware of these typical performance patterns so that they can better manage their expectations and wealth when trading. As individuals understand that exchange rates tend to move in a random manner and that predictive ability may be very short-lived, they will learn to better manage their risk and adapt to changes in market conditions. The third contribution of my thesis underscores the importance of accounting for market volatility when making trading decisions. In general, market turbulence may create potentially profitable opportunities; however, extreme volatility can also be detrimental to performance. Hence, individuals should be constantly aware of the current state of the market

to better manage their risk exposures. Moreover, if past volatility can be used to predict future volatility, such information can be used to the advantage of the trader to improve performance by trading only when the likelihood of success is relatively high. This analysis links the literature on trader performance, which predominantly focuses on the endogenous characteristics of the individual, to the literature on the exogenous dynamics of market volatility. Investigating the relationship between the endogenous and exogenous factors would allow us to better understand the performance and behaviour of traders and encourages further research to improve traditional financial models to include both factors.

The final contribution of my thesis highlights the behavioural biases of skilled traders and how they affect performance using a novel perspective. To the best of my knowledge this is the first study to investigate multiple behavioural biases simultaneously in the context of retail FX traders. I show that common behavioural biases such as herd initiation, disposition effect, sensation seeking, inconsistent behaviour, and information advantage can explain whether certain traders possess superior trading skill. By understanding these behavioural biases and how they affect performance, individual traders can learn to be aware of whether they are likely to exhibit these biases and take precautionary measures to avoid being subjected to the negative effects associated with them. For instance, traders exhibit the disposition effect when they realise small gains and hold on to losses. A trader who realises this can learn to avoid closing winning positions prematurely and limit their losses using stop loss orders. These behavioural patterns can also be used by brokers to categorise clients into

different performance groups in order to hedge against those who are likely top performers based on their behavioural characteristics.

In summary, this thesis underscores the heterogeneous characteristics of individual retail FX traders and calls for future work to further investigate the different attributes that shape the retail foreign exchange market.

Section 2. Literature Review

2.1 Heterogeneous Traders

In finance, heterogeneity is the notion that traders' behaviour is not always rational — in other words, traders do not share common beliefs about the market which may be due to information asymmetry. If market participants differ in behaviour and in the level of information, different expectations should occur, validating the existence of heterogeneity. If financial markets consist only of homogeneous agents with the same forecasting beliefs and information, then there should only be directional/systemic markets, which is clearly not the case according to observational evidence.

2.1.1 Asymmetric Information as a Source of Heterogeneity

Asymmetric information is present whenever one market participant has greater material knowledge than another. Asymmetric information is incorporated into the market over time in a non-uniform way. This creates an imbalance of power in transactions and causes asymmetry. Even if information is in the public domain, participants tend to interpret information asymmetrically according to their own preferences or beliefs.

Grundy and Kim (2002) and Biais et al. (2010) contended that asymmetric information can be a source of heterogeneous expectations among traders. The existence of private information through price changes provides a positive variability creating a heterogeneous economy. Price variability can change

significantly from the influence of asymmetric information (absence of change in supply or the arrival of information beyond those already observed).

Despite nearly homogenous information-processing systems, investors attained different levels of access to information sets related to the current state of the financial markets (Lucas, 1973; Kyle, 1985; Mankiw and Reis, 2003; and Carroll, 2003). In general, investors do not process macroeconomic news in a standardised way, within the same time-frame. It is assumed that market participants absorb market information in discriminatory ways, best suited to their personal circumstances. Therefore, market participants reach different conclusions and form vastly different market expectations, despite the fact that they are exposed to the same set of publicly available information.

De Grauwe and Grimaldi (2005) defined heterogeneous market participants as agents who possess incomplete information and have different opinions about future market dynamics within financial markets. This theoretical model allows for agents' heterogeneous beliefs. It assumes that investors use different forecasting rules and they can switch to the most profitable rules after evaluating relevant probabilities. Similarly, Iori (2002) noted that heterogeneity ensures that traders do not make the same spontaneous decisions.

Macdonald and Marsh (1996), Laster et al. (1999) and Patton and Timmermann (2010) concluded that heterogeneity also arises because forecasters do not always provide all the relevant data since they consider this information to be private. Speculative market participants can be divided into different expectation categories with distinct degrees of heterogeneity. Therefore, heterogeneous beliefs reflect the assumption that agents have an exponential function with

different valuation expectations. In an earlier paper, Goodman (1979) showed that Foreign Exchange (FX) investors are heavily reliant on technical analysis, which can raise the level of heterogeneity among them — especially if there is a propensity for other market participants to implement fundamental analysis in their trading decisions. Goodman demonstrated that the foreign exchange market is inefficient, with strong evidence that technically-oriented services have strong predictive performance and that speculative runs do occur. In other words, historical, technical market information can be used by traders in a speculative manner to predict future foreign exchange prices. Economically-oriented foreign exchange rate forecasting services were found to be inaccurate with a lack of conclusive evidence that they can effectively manage foreign exchange exposure. A similar conclusion was reached by Frankel and Froot (1990) and De Grauwe and Grimaldi (2006). Traders have a tendency to use forecasting techniques that can lead to “excessive volatility” which reflect heterogeneous beliefs or asymmetric information.

Kandel and Pearson (1995) and Næs and Skjeltorp (2006) discovered that traders’ heterogeneity is a catalyst that intensifies the volume-volatility relation. They provided empirical evidence that “the assumption that agents interpret information identically is overly restrictive” and that agents have different interpretations of the same public information. To a limited extent, the volume-volatility relation is explained by the disparity in ‘beliefs’ amongst market participants or by the existence of asymmetric information.

As such, a significant portion of the literature stresses that market imperfections and individual behavioural tendencies lead traders to arrive at different decisions,

even though they might be exposed to the same set of information. This is the result of an individual's endogenous capacity and thought-process, which produces a unique decision, resulting in heterogeneous expectations of the market.

2.1.2 Heterogeneity in Trader Behaviour

Heterogeneity can arise because individuals respond differently to the same event, as a result of personal biases. These biases have a direct impact on the trading characteristics of the trader's strategy. For instance, Keim and Madhavan (1995) used a unique dataset of equity transactions from 21 institutions and provided evidence that liquidity traders (indexers, etc.) prefer to use market orders, while investors (whose information value decays), slowly use limit orders. As a result, institutions in their sample differed in their trading styles and motivation.

Other researchers argued that heterogeneity can be observed by categorising individuals according to their behavioural biases. For example, Cabrales and Hoshi (1996) divided investors into "optimists" who expect prices to go up and are risk-takers, and "pessimists" who prefer to trade more conservatively. In this way, the model with heterogeneous beliefs is useful in explaining various anomalies observed in financial markets.

Researchers, including Lasselle et al. (2005), Koutmos (2012), and Goldbaum and Zwinkels (2014), argued that individuals can generally be categorised as either rational utility maximisers (adaptive traders who respond to trading activity conducted by other market participants), or as naive traders (non-adaptive

traders that do not). This categorisation is based on the notion that some individuals are skilled and able to use market information effectively to make informed decisions, while others take a reactive approach to past information or simply trade on sentiment. Such differences in heterogeneous trading behaviour help to explain the wide spectrum of financial phenomena such as excess volatility, market bubbles and violent corrections in market prices of all asset classes, including stock markets. Furthermore, Locke et al. (2000) examined professional futures traders and found that heterogeneity arises because agents have different trading skills and knowledge. Differences in trading activity and trader success is due to the disposition effect, which is mostly found among the less successful traders. In particular, the authors found that the least successful traders hold on to losses for longer time frames compared to more successful traders, who quickly realise and limit losses.

The quantity and quality of knowledge an investor has can directly impact their behavioural biases. For instance, Goodfellow et al. (2009) used data from the Polish stock market and showed that individual investors tend to 'herd' (i.e. tend to trade in the same direction) more than institutional investors — their actions are often irrational and they tend to underperform — while institutional investors trade according to market fundamentals (Wermers, 1999; Sias et al., 2001; Kim and Wei, 2002; Bushee and Goodman, 2007; Schmeling, 2007) and achieve significantly different trading performance compared to retail investors.

While the above-mentioned studies look at these biases in a static manner, others examine how biases dynamically change over time. Ito (1990) argued that individual biases may be driven by a slow learning process, such that traders

adjust their strategies based on their past activity. Ito found significant evidence of heterogeneity in expectations among forecasters over the duration of the study. Similarly, LeBaron (2001, 2003, 2012) found that the level of market volatility is directly impacted by the level of heterogeneity in the learning ability of market participants. Feedback traders (positive feedback momentum and negative impact contrarian) increase volatility which increases the required rate of return. If the expected return is not impacted, the rate of demand for shares will decrease. Higher volatility will cause prices to move away from the fundamental values affecting the demand for fundamental traders.

In general, the literature shows that endogenous factors and processes, such as knowledge and learning, can significantly alter an individual's behaviour and ultimate decision. This means that, even with the same set of information, traders may arrive at different conclusions due to the way they process that information, learn from it, and adapt their behaviour accordingly. Given the evidence in the literature supporting this argument, one would expect that traders' expectations will be significantly diverse thus creating a persistent heterogeneous marketplace. As such, financial models should incorporate this heterogeneity to better capture market dynamics and explain the differences in performance among traders.

2.1.3 Market Impact on Heterogeneity

Pyo (2014) argued that heterogeneity is prevalent in all economic areas and ignoring it would result in a lack of proper micro-foundation for explaining aggregate outcomes (Kirman, 1992). The author proposed a stock market model

that incorporates different types of stock trading behaviour in relation to market events. The results showed that stock market performance metrics are sensitive to different types of traders (dividend trader, technical trader, and network trader) and memory length i.e. that the current firm profitability relative to past profitability inherently involves the selection of an extent of past data usage. Moreover, Yamamoto and Hirata (2012) investigated the impact of a country's structural economic changes, including global financial crisis influence and monetary policy, on forecasters' expectations. By categorising market participants in their sample into buy-side and sell-side professionals, they were able to examine the determinants of expectation heterogeneity or dispersion. Both buy-side and sell-side professionals possess different information subsets with different interpretations of the same information in their forecasts, contributing to expectation heterogeneity. They demonstrated that when expectations are formed interactively this contributes to heterogeneity expectations in the Japanese stock market. Beine et al. (2007) mentioned that aside from interventions, heterogeneity could be born from uncertainties surrounding the US economy, that can subsequently influence exchange rates and affect both DEM-EUR (German mark and Euro) and DEM-USD (German mark and United States dollar).

In a more recent study, Lim et al. (2016) found that foreign participants may act heterogeneously in different countries' financial markets. The authors examined heterogeneity among different types of foreign investors in the stock market: foreign institutions, foreign individuals and foreign nominees and how they affect the Malaysian market. Foreign investors were found to have superior skills in

processing systematic market information thereby improving the information environment of the local exchange.

The evidence in the literature supports heterogeneous beliefs arising from traders having different occupations, roles, and investment objectives. Thus, given an individual's trading mandate, their expectations may differ from those of other market participants. It follows that every individual has a unique investment goal, thus perceptions of the market are likely to be heterogeneous.

2.1.4 Heterogeneity in Forecasts and Trading Strategies

Rekik et al. (2014) stated that heterogeneity in forecasts is able to create market instability and complicate pricing dynamics. Using the Artificial Neural Networks learning mechanism and creating an artificial stock market, they showed market participants having heterogeneous beliefs and preferences. Specifically, the authors showed that the irrational behaviour of investors explains many financial anomalies, which cannot be explained by traditional market models. The authors built a model comprised of three types of investors: 'fundamentalists', 'non-fundamentalists' and 'loss-averse' investors. As such, the difficulty of prediction arises due to the complexity and non-linearity of investors psychology. Consequently, the Artificial Neural Networks learning mechanism takes on the role of traders, who generate expectations about future market movements, and executes orders based on these expectations. The findings showed that the existence of heterogeneous agents with different expectations provides a better understanding of the price dynamics in financial markets.

Gandhi and Padial (2014) proved that belief in heterogeneity affects returns, where they showed that the majority of the population consists of canonical traders (70%) who hold virtually homogenous beliefs, with the remainder of traders exhibiting significant levels of belief dispersion. Moreover, Tan et al. (2015) mentioned that due to arbitrageurs' heterogeneous beliefs regarding the fundamental value of a security, traders tend to “ride the bubble”, instead of correcting the asset's price. The population in their analysis was divided into two major groups of players in the markets: rational arbitrageurs and noise traders. Their model assumed that arbitrageurs used varying levels of leverage, which meant traders were experiencing variability in pay-offs and optimal waiting periods. In a related study, Naimzada and Ricchiuti (2014) concluded that heterogeneous beliefs about fundamental asset values could lead to market instability (chaotic price fluctuations). They showed that there are interactions and correlations between agents with the same rules, but with different beliefs in fundamental asset values. Using survey data of foreign exchange market expectations, Boswijk et al. (2007) and Goldbaum and Zwinkels (2014) classified responses into two groups: the fundamental strategy “by which predictions concerning future exchange rates are based on exchange rate fundamentals” and the chartist strategy “by which market-based information serves as a predictor of future exchange rates”. The authors concluded that the cause of heterogeneity in the forecasts, is the switching between fundamental and chartist strategies. Proaño (2013) also noted that chartist and fundamentalist types of forecasting can affect financial markets. Proaño assumed that FX traders are following two types of behavioural rules: the fundamentalist rule (taking into account only certain macroeconomic fundamentals) and the chartists or technical

analysts (taking into account only past developments of the nominal exchange rate). Furthermore, Menkhoff and Schmeling (2010) examined individual interbank market participants and the reaction to the counterparties by analysing the counterparties' direction and size of order flow. In particular, they found evidence that large and small traders differ in their use of information. Large traders react strongly to publicly available information whereas small traders rely on private information. Therefore, public information is a strong determinant of individual trading decisions.

Several studies have investigated heterogeneity based on the type of strategy adopted by traders. For example, Beine et al. (2009) observed heterogeneity among the chartists while Kaltwasser (2010) found heterogeneity among fundamental traders. Kaltwasser (2010) developed a model that applies to heterogeneous agents. It assumed that institutional traders and large banks have different beliefs about fundamental prices. The author also concluded that there is "No doubt, traders live in a world where trend followers do exist". In another study, Pyo (2014) categorised traders into three different theoretical types: dividend traders, technical traders, and network traders, depending on the factors chosen (firm profitability, past returns or the investment behaviour of other agents). Furthermore, the author implied that stock market performance metrics are very sensitive to investor type and memory length.

In a more recent study, Chien (2015) distinguished between passive traders (holding fixed portfolios of stocks and bonds) and active traders (portfolios adjusted in response to changes in investment opportunities in the markets). It was observed that active institutional traders frequently generate greater profits

than passive traders while different trading strategies result in a strong level of heterogeneity in financial markets.

The literature presents evidence that heterogeneity arises due to traders adopting different trading strategies. As such, every specific strategy or trading philosophy will likely result in a different trading decision, thus leading to a heterogeneous population as long as traders choose non-similar strategies. One can expect that the wider the range of trading strategies available to traders, the greater the degree of heterogeneity.

2.1.5 Heterogeneity in Risk Tolerance

Several studies have investigated heterogeneity from a risk perspective. For instance, Shefrin (2001) argued that heterogeneity in risk tolerance is different from heterogeneity in beliefs or expectations. The author proposed a model in which traders have different expectations, risk tolerance levels and time horizons — finding that traders become more risk tolerant during upward trending markets.

On a related note, Mankiw et al. (2003) argued that ‘disagreement’ may be a key to macroeconomic dynamics because many macroeconomic models assume market participants will form the same expectations from the same information. They established that expectations are not homogeneous and thus the models’ assumption was rejected. Hence, the amount of disagreement varies over time and some people form expectations based on outdated information (the sticky-information model).

In a more recent study, Bougheas et al. (2015) conducted an experiment to examine investors’ risk-taking and information aggregation in groups who face a

common risk. Their analysis had two main findings. First, the behaviour of most investors is consistent with Bayesian rationality; however, several subjects showed significant reverse confirmation bias. This means that these individuals seemed to place less weight on external sources of information when it was in consensus with their private signals, and gave more weight to conflicting external information that differed from their own private conclusions. Moreover, this tendency is more pronounced when individuals were able to communicate freely. When communication is restricted, the evidence on reverse confirmation bias declines to the same level as confirmation bias. This phenomenon could be interpreted as individuals acquiring a probability heuristic during discussions with other market participants. The second main finding of this study was that when individuals communicate freely there is a high consensus among decisions. This may be due to the persuasive arguments of certain individuals and their ability to influence the decisions and thought processes of other market participants.

The evidence in the literature supports variations in risk tolerances among traders, which mainly arises from the overall state of the market and how an individual's expectation relates to the market consensus. In general, when the market is performing well, traders are willing to tolerate more risk. This suggests that risk tolerance of an individual is not static, but rather changes as a function of market conditions. Such a statement implies that risk management practices should also be dynamic and be adapted to current market conditions.

2.1.6 Empirical Literature on Heterogeneity

2.1.6.1 Heterogeneity at the Macro Level

There is a mass of literature that examines heterogeneity in foreign exchange rates at the macro level. The general argument of these studies is that there are various competing models and types of traders with varying expectations, whose trading activities determine the equilibrium exchange rate. For instance, Bacchetta and van Wincoop (2006) studied the influence of heterogeneity on exchange rate dynamics. The authors applied a standard monetary model of exchange rate determination, incorporating money market equilibrium, Purchase Price Parity (PPP) and interest rate parity. The authors identified two drivers of heterogeneity: 'dispersed information about fundamentals' and 'non-fundamentals'. Specifically, the exchange rate was found to be driven primarily by fundamentals only over longer horizons, with only a small number of non-fundamentals being the main source of exchange rate volatility when information is heterogeneous.

Ahrens and Reitz (2005) built on the work of Frankel and Froot (1986) and proposed the chartist and fundamentalist regime-switching model. DM/US German mark/dollar exchange rates from 1982 to 1998 (daily and monthly three-month forward exchange rate returns) were used for empirical examination. The authors used data from the International Monetary Fund's (IMF) International Financial Statistics to calculate the fundamental value (PPP). Both the chartist and the fundamentalist parameters for forecasting were tested. Under the premises of their model, spot market speculation consisted of a covered interest

transaction and forward market speculation. For the time period covered (January 1982 to December 1998) the empirical results showed that daily German-US forward rates could be explained by the heterogeneous expectations exchange rate model. In a related study, De Grauwe and Grimaldi (2005) examined chartist and fundamental models of spot rate market forecasting and the decisions to switch between them. The authors created an exchange rate model that showed non-linearity in the dynamics of the foreign exchange market. The main reason for this is the existence of transaction costs in goods markets. Investors have different expectations in this model and do not always act rationally. Firstly, the authors defined the fundamental exchange rate, assuming that it behaves like a random walk without drift. Then, two types of traders were distinguished: 1) fundamentalists who forecast the future market rate movement with respect to the fundamental rate, following a negative feedback rule, and 2) chartists who follow a positive feedback rule, extrapolating past exchange rate movements and inferencing into the future. The authors used the method proposed by Brock and Hommes (1997, 1998) to measure the profitability underpinning different types of traders. According to the amount of profits, investors may decide to change their trading style. The risk associated with the forecasting rule of the chartists and fundamentalists and their combined expectations, “the market expectation of the exchange rate change” was also estimated, with transaction costs also being taken into consideration. The authors showed that even minimal market disturbance could influence the exchange rate dramatically (a chaotic region was found during the sensitivity analysis). Another chartist-fundamentalist model was proposed by Manzan and Westerhoff (2007). They assumed that traders have heterogeneous expectations of the exchange rate and are able to switch between

two regimes according to their preferences. The authors used monthly exchange rates from the beginning of 1974 to the end of 1998, for six currencies: the German mark (DM), Japanese yen (JY), Canadian dollar (CD) French franc (FF) and the British pound (BP) against the US dollar. Exchange rate series were simulated for all used currencies and results compared and contrasted to the alternative random walk model. The long-horizon tests were significant (bearing a strong prediction power), unlike the short-term results.

De Jong et al. (2010) studied the heterogeneity of agents' expectations with different beliefs and levels of information. Their database consisted of seven monthly bilateral exchange rates for currencies of countries that became European Monetary System (EMS) members between March 1979 and December 1998. Unlike the other authors, De Jong et al. (2010) distinguished three types of investors: fundamentalists and two types of chartists (the Auto-Regressive (AR) and the Moving Average (MA) types), with various forecasting rules being formulated for each type of trader. Similar to De Jong et al. (2010), the authors found that traders try to select the most profitable strategy for each period.

From a different perspective, Rekik et al. (2014) proposed an agent-based model to explain price dynamics in financial markets. The authors argued that financial markets consist of agents with different expectations and who exhibit both rational and irrational behaviour simultaneously. The authors developed an artificial stock market and recorded more than 1,000 observations, to conclude that all factors (fundamentalist, anchoring heuristic, etc.) play a role in affecting price dynamics of assets. The authors examined both the degree of heterogeneity amongst

investors and its impact on broader pricing dynamics, to conclude that both fundamental investors and non-fundamental noise traders interact to affect financial markets at the macroeconomic level. It is this interaction which is the cause of asset price fluctuations. In other words, the authors provided evidence of the correlation between individual traders' behaviour and financial market dynamics.

Other empirical papers argue that heterogeneity in foreign exchange rates is directly driven by heterogeneity in trader expectations and forecasts, which arises from traders having incomplete or different information sources. Menkhoff et al. (2009) showed that exchange rate changes and inefficient pricing are able to explain the heterogeneity among forecasters. They use individual expectations from a market survey from the Centre for European Economic Research (ZEW). The survey provided detailed information on a census of 6-month forecasts sourced from a wide-range of financial market professionals. The sample contained expectations for the US-dollar/euro, GB-pound/euro and JP-yen/euro exchange rates, with about 300 responses on average from December 1991 until August 2006. They used a C&F (chartist and fundamentalist) approach from a different perspective — by calculating dispersions i.e. their measure of heterogeneity in exchange rate expectations determined which factors affect the behaviour of chartists and fundamentalists. Exchange rate 'misalignments' and exchange rate changes helped to explain heterogeneity.

Evans (2002) demonstrated that in the DEM/USD market, the high level of volatility is caused by strong market heterogeneity. Using a unique dataset of trading activity for the Deutsche mark/dollar (DM/\$) in the spot FX market from

May 1, 1996 to August 31, 1996, Evans implied that traders' trading decisions are based on incomplete and heterogeneous information. All data was distinguished on common-knowledge (CK) news and non-common-knowledge (NCK) news. CK is public information that is interpreted homogeneously by everyone. NCK news is public and private data which creates no consensus among dealers as to its influence on underlying exchange rates. NCK news affects trading patterns and the whole distribution of transaction prices, while CK news affect only the latter. The author created a model to examine the origins of exchange rate dynamics using both types of information and a sampling component that presented the dispersion of an equilibrium transaction price distribution at each time point (i.e. the heterogeneity in trading decisions making process in markets that lack transparency). According to the results, between 17 and 80 percent of the variance in short-term price changes under normal market conditions was caused by this component. The influence of CK news reaches 15 to 40 percent for short-term price changes, and from 20 to 90 percent for long-term changes. Approximately 80 percent of the variance in permanent price shocks comes from NCK news. Specifically, information about Deutsche mark/dollar (DEM/USD) was observed from May 1 to August 31, 1996, provided by the Reuters D2000-1 system using 79 full trading days, and containing 255,497 trades.

Another set of studies examined how market stimulus plans, such as central bank interventions, impact on heterogeneity in foreign exchange markets. For instance, Beine (2003) measured volatility expectations and the effects of central bank (CBI) actions on exchange rates through the use of the Markov switching model. DEM/USD and the JP-YEN/USD markets were observed from 1985 to

1995 (Philadelphia Stock Exchange and Datastream). Evidence of heterogeneity was present because of different investor reactions to central bank interventions (some investors responded in a reactionary fashion, some ignored the event(s) and some took predictive trading decisions). The author also showed evidence of heterogeneity between the investigated currencies and the stress related to the role of policy credibility.

Similarly, Beine et al. (2007) investigated whether there exists an influence of official foreign exchange interventions on forecast heterogeneity. Interventions from several central banks were observed (the Bank of Japan, the Federal Reserve, the European Central Bank (ECB) and the Bundesbank). They used monthly survey data forecasts from two periods: 1992-1994 and 1996-2001. Generally, official interventions drive forecast heterogeneity. Analysing the DEM-EUR/USD market, the authors found that heterogeneity arises due to unexpected interventions (the difference between actual and expected interventions) while in the USD/JPY market, heterogeneity arises due to expected interventions as predicted by rumours during the four days before the actual intervention.

The literature above presents significant evidence highlighting that heterogeneity in the long-run is driven by different expectations of macro and government factors. This long-run heterogeneity can be incorporated into foreign exchange pricing models to estimate the variation in expectations around a certain consensus.

2.1.6.2 Institutional Traders and Forecasters

Many researchers have examined heterogeneity among large institutional traders or forecasters in the foreign exchange markets (Ito, 1990; Lyons, 1991, 1993; Frankel and Rose, 1994; Elliott and Ito, 1999; Evans, 2002; Bacchetta and van Wincoop, 2003; Bénassy-Quéré et al., 2003; De Grauwe and Grimaldi, 2006; Dreger and Stadtmann, 2008; Reitz and Taylor, 2008; Menkhoff et al., 2009; Goldbaum and Zwickels, 2014).

One of the most popular studies was conducted by Ito (1990), who collected data from the Japan Centre for International Finance (JCIF) of bi-weekly surveys and concluded that foreign exchange market participants are heterogeneous. Ito analysed the yen/dollar exchange rate expectations using the data of two years for 44 different institutions which include banks, brokers, securities, trading companies, export-oriented organisations, life insurance firms and import-oriented industries. Ito (1990) showed that heterogeneity exists among market participants for different time horizons. In addition, Ito demonstrated that the reason for the existence of heterogeneity lies more in the biases from individual effects than idiosyncratic ratios of lagged variables. In other words, heterogeneity does not appear because of different investors' reactions, but rather, it is a constant bias. Ito also suggested that heterogeneity may be attributed to the behaviour of market participants mostly due to traders' slow and lagging learning process. The methodology was based on the assumption that exchange markets' information is generally public and accessible. Similarly, other studies have shown the main cause of heterogeneity in the foreign exchange markets is due

to idiosyncratic interpretations of widely available information, thereby leading to significant differences in forecast accuracy.

In their co-study regarding noise trading influence on exchange rates, Froot and Frankel (1989) showed that expected heterogeneity arises with sufficient numbers of unsophisticated traders providing significant noise trading. They used survey data information on exchange rate expectations, sourcing their data from three surveys: American Express Banking Corporation of London (1976 and 1985), Economist's Financial Report of London (at regular six-week intervals since 1981) and the Money Market Services (MMS) of California (every two weeks beginning in November 1982 and every week beginning in October 1984). Their study focused on the question of whether the systematic portion of forward discount prediction errors could capture a time-varying risk premium and expectations. As for heterogeneity, they checked if there exists a single expectation, which is used by all agents. The results showed that different survey responders reported different forecasts, indicating the presence of heterogeneity in the investigated data. It was also determined that measurement error in the data was random. They found that investors would do better if they reduce their expectations of depreciation (fractional reduction).

Macdonald and Marsh (1996) believed that heterogeneity is a crucial element in studying the behaviour of foreign exchange rates. They examined forecasts from corporate entities, professional agencies and institutions from G-7 countries to estimate the degree of heterogeneity (if any) present among them. Three-month and twelve-month forecasts for the three exchange rates were observed (from October 1989 to September 1992). Using two forecast datasets gave them the

ability to recognise variability in traders' forecasting performance over the two periods. Using Ito's (1990) simple and robust test for forecast differences detection, they found that both the three- and twelve-month forecasts have a significantly strong level of heterogeneity. In terms of forecasting prediction, forecasters are seemingly more accurate at relatively long-term horizons. This shows that traders behave very idiosyncratically when participating in foreign exchange markets. Macdonald and Marsh also analysed the quality of forecasts and concluded that good forecasters can sustain their accuracy only for a single currency pair. In addition, the authors find that short-term forecasters also tend to be good at forecasting long-term exchange rates.

In a later study, Ito and Elliott (1999) examined traders' behaviour in the yen/dollar market using micro survey data. They used exchange rate forecasts and calculated profits based on a positive trading rule. The authors used an updated version of the dataset used by Ito (1990), containing individual forecasts of 42 companies with future spot yen/dollar rates for one, three, and six-month horizons from May 1985 to May 1996. During the 1985 to 1987 period huge differences in the forecasts were documented (from 15 to 30 yen per dollar for the one-month expectations and from 25 to 70 yen per dollar for the six-month expectations). Potential profits generated from decisions based on these forecasts are highly variable thus indicating significant risk in using such strategies. The authors concluded that this area could be further investigated since the difference between the profitability behaviour of the random walk model forecasts and the respondent forecasts suggest that there is potential in these models (i.e. not limited to static expectations with random noise).

Bénassy-Quéré et al. (2003) examined the expectation formation process of individual foreign exchange market participants. Data from 40 leading foreign exchange forecasters/dealers was used, in addition to forecasts from the Consensus Economics of London panel survey from January 1990 to December 1994. The 3 and 12-month horizons were taken for the US dollar bilateral rates of the DM, yen and pound sterling, with Swamy and Fisher tests for the homogeneity of all individual coefficients. The authors estimated three basic expectation models: the extrapolative model (forecasters are chartists), the regressive framework (the exchange rate always returns to the equilibrium value, with independent movement), and the adaptive model (learning process where agents learn the 'true' level of the variable rather than its underlying process). Combining these models, the authors created a hybrid. The results showed that 13 to 61 percent of individual coefficients differ significantly from the panel average (depending on the individual coefficient and the exchange rate) in the extrapolative model. The results also indicate approximately one-third of all traders — in the regressive framework — and significant (but weaker than in other models) level of heterogeneity in the adaptive model. The 12-month horizons were found to be more homogeneous in comparison to 3-months. As for the combined model, it also showed the lack of individual homogeneity. The authors concluded that the coexistence of various types of agents may be the cause of heterogeneity, and that heterogeneity in the observed financial markets is very significant. In a related study, Beine et al. (2007) estimated heterogeneity of trader expectations using a sample of 100 forecasters from 1992 to 1994 and another sample from 1996 to 2001, obtained from Consensus Forecasts (London) monthly surveys for the Japanese yen, the Deutsche Mark and the Euro

against the US dollar. The sample contains monthly surveys of analysts from banks and forecasting institutions of 1 to 24-month forecasts. Heterogeneity was found to be higher over a longer term horizon. Cross-section coefficients of variation were also used to measure individual forecast range. The lowest result was 2% in DEM-EUR market for three months forecasts, while the highest result was 10% (YEN, 12 months in 1998). Central bank interventions can be viewed as a possible means of generating different market opinions. For the DEM/USD and EUR/USD exchange rates, it was suggested that unexpected interventions raised information heterogeneity while interventions in the JPY/USD market produced mixed outcomes.

Using a different approach, Menkhoff et al. (2009) classified subjects as either chartist or fundamentalist to explain heterogeneity in exchange rate expectations. The dataset used was obtained from the Centre for European Economic Research (ZEW) and the Deutsche Bundesbank, and contained 300 professionals in three major exchange rates (US dollar/euro, GB-pound/euro and JP-yen/euro) over 15 years from December 1991 to August 2006. The results showed that uncertainty among fundamentalists and a shift from dominating fundamentalists to the minor group of chartists has a positive correlation to heterogeneity. The main reasons for heterogeneous behaviour were exchange rate volatility, macroeconomic variables and (to a lesser degree) the risk premium influence. The risk captured by lagged exchange volatility explained heterogeneity, only and if there is no control for the three determinants: 1) uncertainty among fundamentalists, 2) a shift from dominating fundamentalists to the minor group of chartists and 3) whether these measures carry a risk premium.

Reitz et al. (2010) investigated heterogeneity in the Japanese currency market. Similar to Ito (1990), the authors examined the JPY/USD market, where they obtained their data from Consensus Economics Inc. The survey included monthly forecast spreads across a sample from October 1995 to December 2007, including 146 monthly forecasts from 31 individuals. They found a correlation between forecast dispersion and past exchange-rate volatility, such that heterogeneity increased with growing misalignments. The authors also found that heterogeneity expectations softened during periods of foreign exchange interventions by the Japanese Ministry of Finance. The study concluded that the magnitude of the interventions has a greater significance compared to the frequency of interventions, and that the former can greatly reduce heterogeneity in forecasts.

Goldbaum and Zwinkels (2014) examined how expectations are formed by financial institutions operating in the foreign exchange market. They obtained forecast data from participating international financial institutions: a total of 146 monthly observations, sourced from 31 companies, forecasting the Euro/Dollar and Yen/Dollar exchange rates over one, three, and twelve-month time horizons for the period of November 1995 to December 2004. A recursive and estimation algorithm was developed utilising the surveyed expectations. These responses were classified into two groups: the fundamentalists who were found to have mean-reverting expectations and the chartists who were found to have contrarian expectations. The switching model was very useful in explaining heterogeneity in the forecasts. Permitting panellists to switch between models improved the model's accuracy predominantly over short forecast horizons. In addition, as the

forecast horizon increased, the fundamental model was found to be more popular. Finally, the results showed that the model of choice included a combination between period-specific and individual-specific determinants.

Hsu et al. (2016) studied the heterogeneity of information, which are traders' various responses to the same information (also called "trading due to the noise information"). Their study used data from the Taiwan Economic Journal database including daily closing prices, trading volume of each TSE stock, daily closing prices, number of the trading units and the trading volume of TSE Taiwan Capitalisation Weighted Stock Index (TAIEX) for the period of January 1995 to December 2008. The authors proposed a new theory regarding the heterogeneity of trading information and price-volume relationship. The empirical evidence demonstrates that stock price reversals often occur due to extremely large trading volumes; however, an abnormally large volume is not always the cause of price reversals. Their results strongly support the view that this is due to heterogeneity of trading information among traders during price reversals.

The literature on institutional investors shows that there is significant heterogeneity among these entities. This may be due to institutional investors possessing unique private information, or proprietary forecasting models, which produce significantly different expectations. Nevertheless, these factors may not be common drivers of heterogeneity among retail traders since individual traders are less likely to possess superior information due to their limited resources to both gather and analyse complex sets of information. However, the abovementioned studies highlight that heterogeneity is not only present among

noise traders, but rather can be found at the institutional level, where resourceful entities can have different expectations of future market movements.

2.1.6.3 Retail Traders

Hayley and Marsh (2016) studied the quality of traders' decisions in the retail FX market. The main aim was to determine if traders who are "learning by doing" (obtaining the experience by trading themselves) trade with better results over time. The authors used data from an anonymous online retail foreign exchange trading platform, including data such as number of trades, total value of trades, total value of positions that remain open after the 9pm reconciliation, capital injections and extractions, realised profit (loss), and personal information like the age and location (city and country). The scope of the data was from 4 January 2010 to 29 June 2012. The study incorporated data from 95,617 unique traders and examined more than 4.8 million trader-day entries. Heterogeneity was measured as the investors' performance, on a daily basis and compared to previous trading history. The authors concluded that certain types of traders always perform better than others, with one key finding being that older, more experienced traders responded differently to positive and/or negative market stimuli compared to younger traders. Therefore, there is some evidence supporting the existence of cross-sectional heterogeneity in retail FX markets, as per when using a variant of the Heckman selection model to estimate this phenomenon. The authors found no evidence that retail FX traders learn to trade more efficiently, although they did conclude that traders learn about their innate abilities (if they gain income from trading, they will continue investing and vice versa). They argued that foreign exchange traders with different level of abilities

invest differently, where beginner traders are more inclined to trade smaller amounts or less frequently compared to their more experienced counterparts, especially when the trading day was unsuccessful. Nevertheless, the study focused more on the learning ability rather than on the heterogeneity itself, although it was examined as a part of traders' learning behaviour.

Similar evidence of heterogeneity has also been found by Abbey and Doukas (2015), using a sample of 428 foreign exchange traders from 2004 to 2009 and found that around 25% of traders exhibited skill and significantly outperformed a four-factor currency model, even inclusive of transaction costs. The authors also showed that traders in the heterogeneous population have a stronger tendency to quit.

The literature presents evidence showing that individual retail FX traders exhibit heterogeneity in performance, and that such heterogeneity varies over the career of the trader. Hence, traders who have only just started their trading careers are likely to trade differently than those who have accumulated experience and learned to adapt to changing market conditions and varying market volatility. It follows that it is important to investigate heterogeneity among subgroups of individuals based on their trading career phase and characteristics, as I do in this thesis.

2.2 Trading Skills

2.2.1 Identifying Skilled Traders

As mentioned previously, there is evidence of heterogeneity among retail foreign exchange traders that challenges classical finance theories. Given that there exists significant heterogeneity among retail FX traders, one would expect these traders to exhibit different levels of skill. According to Ramadorai (2006), good performing currency traders are those who pay attention to their returns from trading, while poor performers pay no attention to returns from trading and receive comparatively lower quality execution from financial dealers. The characteristics of traders in various asset classes linked with currency purchases can accurately identify the objectives of traders and determine heterogeneity among trader types. The author highlighted the importance of empirical analysis to investigate the variation of flows across currency traders as a determinant of trader performance and skill.

Hayley and Marsh (2016) argued that foreign exchange market uncertainty is captured by large statistical variability in exchange rate fluctuations. Given this uncertainty, the authors did not find consistent evidence of positive performance among retail FX traders, which may be due to the fact that exchange rates frequently follow a drift-less random walk.

In an earlier paper, Levich (1979) investigated the variability of unanticipated exchange rate changes over a five-year period, and found that floating exchange rates can have periods of both stable and turbulent trading activity. The study showed that firms and investors cannot take advantage of the currency markets

and earn abnormal returns, given the assumption that foreign exchange markets do not have frequent announcements of fundamental information regarding exchange rates. Moreover, Levich (1979) described how the costs associated with obtaining information can lead to uninformed trading and inefficient markets. As such, profits are correlated with the cost of information, which implies a greater likelihood of informed market participants earning higher profits compared to uninformed agents. If information is not easily and readily accessible then it can be characterised as having an advantageous edge, where excess returns are possible. The study concludes that in foreign exchange markets, where fundamental information is generally disclosed uniformly to the market, there should be no room for excess returns resulting from private information. This echoes the seminal work of Keynes (1930) and Hicks (1975) who argued that rational speculators will not trade unless they can expect to earn abnormal profits.

Pojarliev and Levich (2010) argued that currency returns are unpredictable and uncorrelated to the general market. This implies that agents' skills are crucial in foreign exchange markets, as well as the instruments used to estimate their performance. However, currency managers' returns are in part due to skill, and in part due to varying exposure to risk factors. The study showed that heterogeneity arises due to differences in traders' skill levels and that some managers exhibit better persistent performance stemming from diversification strategies.

From a different perspective, Cornell (1979) discovered that inside information leads to abnormal profits and noted there is a significant difference between informed and uninformed traders in terms of average daily returns. This shows

the extent to which a trader's performance can be influenced by a high level of information asymmetry. The author showed that in contrast to uninformed traders, informed traders accumulate wealth at a greater rate, which implies a growing fraction of the market. If differences in performance can be detected, rational investors should choose informed portfolio managers to manage their funds and in turn the informed portfolio managers should dominate the market. Rational condition implies there is no pattern to error terms. If such a pattern exists, uninformed investors can exploit it to improve their probability of success. The study concludes that uninformed traders believe that there are no mispriced securities.

From an institutional benchmarking perspective, Amiri et al. (2010) and Melvin and Shad (2011) noted several "challenges" for evaluating currency investment manager performance, such as the lack of a currency market portfolio, which can be used as a benchmark, and the lack of "buy and hold" strategies in the FX market. Hence there is no standardised benchmark for evaluating traders' performance with respect to currencies and the foreign exchange market.

I will begin by discussing the empirical findings on 'skill' among retail foreign exchange traders. Given the scarce amount of literature previously published on retail FX traders, I will also discuss some of the most popular papers on institutional foreign exchange forecasters and on the evidence of 'skill' in other markets including futures and equities markets.

2.2.2 Skill Among Retail FX Traders

Abbey and Doukas (2015) examined individual currency investor performance, drawdown, trading and timing abilities. Despite the fact that foreign exchange traders are considered to be extremely risky, they proved that individual traders (about 25%) are able to generate abnormal returns, with a positive relation between agents' performance and trade activity being found as a result of the study. The primary dataset of their research was provided by an online advisory service Collective2.com for individual retail spot currency traders. Collective2 (www.collective2.com) was founded in 2001 and is one of the most established platforms in the industry. The dataset consisted of 428 accounts, 9,282 registered account holders and 78,362 roundtrip transactions from March 2004 to September 2009. Investors were classified as intra-day traders (i.e. those who hold positions open for less than a day) and inter-day traders (i.e. those who keep positions open for more than one trading day). The following trader characteristics of agents were provided: names, account description, the number of contracts opened and closed, P/L, net profit ratio and for further analysis, the following variables were computed: trades per day, daily turnover, transaction costs per contract and the age of an account. To begin, the authors computed the raw daily return of each investor as a sum of all roundtrip transactions and the nominal dollar change in the value of open positions. Using closing spot currency prices for different currency pairs, they calculated the purchase and selling prices of contracts. Consequently, the authors went on to present gross and net returns per portfolio and individual contract (details provided in the methodology section). Also, the authors took into consideration traders' risk-adjusted performance,

providing a passive benchmark model proxied by the Deutsche Bank Currency Return Index (DBCR), raw returns, and a modified version of alpha from the four-factor currency model of Pojarliev and Levich (2012). The four possible factors presented by Pojarliev and Levich are:

- **Carry Strategy:** buying in a low-interest rate currency and investing in a higher interest-rate currency. The risk associated with this strategy (which leads to greatest losses) is fully borne out if the low-interest rate currency depreciates by more than the applicable interest differential.
- **Trend Following Strategy:** investing in currencies with upside momentum financed by borrowing currencies with downside momentum and vice versa. The risks associated with this strategy are sudden reversals of trends of patterns, excessive trading costs and so on.
- **Value Strategy:** investing in an undervalued currency whilst borrowing in an overvalued currency. The risk associated with this strategy is that currencies may become more misaligned i.e. their rates reverting toward the equilibrium (Purchasing Power Parity (PPP)) value, or that the real exchange rate changes consistently with the new PPP exchange rate.
- **Volatility:** this does not reflect the returns of a trading strategy, but does affect the change in foreign exchange volatility. Volatility risk entails opening simultaneous currency positions in spot FX, but also, in other derivatives such as options whose prices are sensitive to volatility.

In the futures market, Hartzmark (1991) studied whether investors' profits were the result of skill or pure luck. Hartzmark argued that the returns of futures traders are generated by a stochastic process. Consequently, the author presents the

“luck hypothesis”, which is based on the observed distribution of the forecasting abilities of traders; given the fact that superior and inferior traders regress toward the mean when comparing early and late period forecasting ability. All models proved that individual traders earn positive and significant gross and raw returns with passive benchmark models, showing that traders gain profits even after commissions (the four-factor model does not show this result). The best score for a gross daily raw return, according to the study, was 1.04% per day, and the worst was 0.25% per day. As for net profits, the highest one was 0.71%, and the lowest -0.57%, according to a net raw return model. The paper concluded that investors are able to generate profits in FX markets, but that transaction costs weigh heavily on their returns. It was also observed that intra-day traders are more successful than inter-day traders, according to all three performance measures. Another finding was that the higher the past returns, the more active trading activity tends to become. One of the possible reasons for significantly abnormal profits amongst individual traders is their proportionately higher propensity for risk-taking behaviour, expressed through their use of higher leverage ratios. In addition, these traders’ trading process resembled rather more a gambling approach than a trading strategy.

In a more recent study, Hayley and Marsh (2016) estimated how traders’ performance is affected by investor participation in the FX market. They found a strong degree of heterogeneity in agents’ profitability levels. They used success ratio as one of the measures (having the limitation of the percentage of profitable days instead of closed trades). The data was provided by an anonymous online retail foreign exchange trading platform. The dataset begins on 4 January 2010

and ends on 29 June 2012. The data consisted of the complete trading history of a random sample of 95,617 unique traders, amounting to almost 4.8 million trader-day entries. Their results showed the average success ratio to be under 50% with very high dispersion. Some traders were unsuccessful on every day they traded, while 10% of traders won three days out of five. The results showed that a high level of average career success in the past can help predict higher future returns. The same success ratio was applied to model the propensity of traders to cease trading altogether. The results showed an inverse correlation between career success and the desire to cease trading.

The above evidence shows that very few traders possess genuine trading skill irrespective of the financial instrument being traded. Moreover, performance of traders is widely dispersed, meaning that there is no consistency across traders and that performance is distributed across a wide spectrum of outcomes. This implies that performance in general is highly random and unpredictable.

2.2.3 Forecasting Power of Trading Strategies

Rules-based strategies have been very popular in the FX market, and they have been shown to significantly outperform the S&P 500 index with a higher Sharpe ratio over all periods (Neely and Weller, 2013). Poti and Siddique (2013) model the admissible amount of predictability corresponding to a broad class of rational currency pricing models, and find that predictability itself is predictable. This challenges the efficient market hypothesis of Fama (1970) but is consistent with microstructure models of FX markets where individual retail traders seek to maximise returns relative to total risk rather than systematic risk alone. Given the

notion that traders aim to generate profits that compensate them for the total risk they are willing to take, many studies have investigated the profitability of trading strategies among FX traders.

One of the early studies was conducted by Levich (1979) who measured investor returns from different forecasters to examine the accuracy of information when predicting future exchange rates. The author observed methods from nine leading foreign exchange advisory services, with Harris Bank providing the data for spot and forward exchange rates for the period January 1967 to February 1979. After testing different forecasting methods and models, the author concluded that most advisory service forecasts are not as accurate as market forward rates. However, the fraction of good predictions was significantly higher than expected. Using the differences in expected forward rate movements, the author showed that traders might only be interested in the sign (whether it is a gain or a loss) of their profits rather than the magnitude. Relatedly, Goodman (1979) applied three measures for predicting a trend, point estimate accuracy, and speculative return on invested capital, in order to investigate the accuracy of trading strategies in terms of forecasting foreign exchange rate movements. The author used ten major forecasting services which included six economics-oriented services and four technically-oriented services, and examined their predictive accuracy for six currencies (French Franc, Canadian Dollar, Japanese Yen, German Mark, Swiss Franc and British Pound) against the US dollar from January 1976 to June 1978. Traders who followed indicators at random were found to be less profitable compared to those that implemented buy and hold strategies (1.12% annually before transaction costs against 2.86% per annum

before transaction costs). Successful forecasting services are predominantly technical-analysis-oriented, and on average return 7.28% and 10.46% annually before transaction costs. Goodman concluded that forecasting abilities play a significant role in earning profits.

Bilson (1981) examined whether there were any possibilities for speculative profits in FX markets by linking the volatility of exchange rates and the existence of opportunities. Using the five major currencies: the Canadian dollar, the Pound sterling, the Deutsche mark, the French franc and the Japanese yen from January 17, 1975, to November 14, 1980, the author found a positive correlation between the volatility of exchange rates, and the level of speculative activity. Specifically, the more stable the market is, the less successful speculators are, which is a conclusion that is contrary to Telser's (1959) findings. Later, Bilson (1987) calculated the investor returns of those who used a speculative strategy in the foreign exchange markets. The study investigated the efficiency of investors' forecasting models compared to the random walk model, using the rate of return and the actual amount of profits. The data consisted of 666 observations taken on the Friday of every fourth week of the spot rate and the one-month forward rate, over the period from July 1974 to January 1980. The data consisted of low-interest rate currencies such as the Swiss franc and high-interest rate currencies such as the Italian lira. In total, the data covered nine currencies (British pound, Canadian dollar, French franc, Belgian franc, Italian lira, Deutsche mark, Dutch guilder, Swiss franc, and Japanese yen). The author examined the speculative model's performance within their portfolios, calculating the gross profits, the expected net dollar profit and the Return on Investment (ROI). The latter was

calculated with the assumption that speculators earn the Treasury Bill rate on the margin, so the net profit is the sum of the speculative activity gains and the interest on the margin minus applicable transactions costs. Ten percent over the four-week span was found to be the best ROI for the observed period, although the model is believed to be profitable only “on average”.

Similarly, Schulmeister (1988) examined speculative profitability using data on the dollar and the Deutsche mark from March 1973 to March 1988. The author showed that technical trading rules increase returns without increasing risks. Further analysis examined the riskiness of technical analysis by testing the mean of the single rates of return against zero, and demonstrated that this type of trading is profitable during the entire period covered (from 1973 to 1986). Despite the fact that the number of losses exceeded the number of wins, the average duration of the profitable positions was longer than that of the unprofitable positions. This can be considered as evidence of Big Hit Ability (BHA), a term coined in a later study.

Levich and Thomas (1993) also used the rate of return to estimate technical trading rules, potentially profitable for investors in the foreign exchange market. The authors used a dataset from I.P. Sharpe & Co., and the International Monetary Market of the Chicago Mercantile Exchange, for five currencies (British pound, Canadian dollar, German mark, Japanese yen and Swiss franc), covering the period from January 1, 1976, to December 31, 1990, using 3,800 daily observations in total. The results showed that different currencies act differently, but from the 1970s to the 1980s the high level of profitability of simple technical

trading models was observable at numerous trading venues. Since the 1990's (possibly due to central bank interventions) the rate of return has declined.

The opportunities for profitable trading in European spot cross-rates were studied by Lee and Mathur (1996). The authors used six different currency pairs (JY/BP, DM/BP, JY/DM, SF/DM, SF/BP, and JY/SF) from data provided by the Knight Ridder Database, from May 23, 1988 to December 31, 1993. The author's calculated daily returns on cross-rates trading and checked if the moving average trading rule is a profitable one. The results showed that only two of the six currencies (JY/DM and JY/SF cross-rates) delivered profits with the use of this strategy. Overall, the results suggest that it is not profitable to use the specified moving average trading rules in European cross-rates.

Levich and Poti (2015) investigated the predictability and returns attractiveness of trading strategies in the FX market. Using currency returns from 1971 to 2006, the authors find evidence that predictability often exceeds an upper-bound "no good-deal" threshold. Moreover, strategies that aim to exploit daily excess-predictability are very sensitive to transaction costs, while strategies that have a monthly time horizon remain attractive even after deducting trading costs.

Trading costs and market volatility can be detrimental to performance and must be taken into account when calculating ex-post performance. For instance, Menkhoff and Taylor (2007) used data from spot trading in equities and currencies, between 2014 and 2015, in the seven largest asset trading centres, to measure investors' return when implementing technical analysis. The authors determined that traders could be profitable despite paying transaction costs and that there is a positive relationship between these returns and level of currency

volatility. They also found that performance of technical models is not consistent over time.

Similarly, in an attempt to account for volatility, Charlebois and Sapp (2007) used daily excess returns data and the Sharpe ratio, from January 1, 1988, to December 31, 1999, for the US dollar-Deutsche Mark spot exchange rate, to measure trading strategy profitability. They concluded that using at-the-money option strategies is more profitable than trading strategies based only on historical exchange rate data and that options appear to contain information about future spot exchange rate movements. Similar to Lee and Mathur (1996), they observed the moving average (MA) trading rule performance. As a result, the MA strategy generated returns (3.42% annually), proving that the foreign exchange market is not an efficient one. Similarly, Villanueva (2007) investigated whether currency excess returns can be used to predict the forward premium, using data from DataStream for the monthly spot rates DEM, JPY, and GBP over the period January 1981 to December 1998. Villanueva defined the success ratio as the fraction of correct predictions, and showed that standard mean square can be used for profit generation.

In general, the results of the abovementioned papers show that technical trading strategies do generate positive returns. This implies an inefficient foreign exchange market which exhibits profitable anomalies that can be exploited by traders. While there may exist profitable market trends in the short-term as shown by ex-post analyses, it may require a truly skilled trader to be able to identify such opportunities as they are happening in real time.

2.2.4 Institutional Forecasters and Traders

Marsh and Power (1996) calculated the performance of 22 forecasters to test if their strategies are profitable and accurate. The dataset used included industrial corporations, commercial and investment banks, Chambers of Commerce and forecasting agencies, from the Group of Seven nations (G7) (six countries overall). The authors compared the Deutschmark, Pound sterling and Japanese yen as traded currencies against the US dollar, for the period September 1989 to August 1992. Overall, their results showed that forecasting strategies are not profitable. Two portfolios were created to estimate investors' performance, with an average expected profit target set for each forecaster at \$100, and actual results tallied thereafter. Converting to the rate of return measure, only 7 of 22 agents showed positive results, and only two demonstrated the significantly positive average profits, set at 10%. With regards to excess profits, only one forecaster had a return significantly greater than zero (5%).

Melvin and Shad (2011) examined currency investment manager performance evaluation. Skill in timing and minimising drawdowns were the generic factors used to differentiate skilled investors. For empirical evidence, the study used the Deutsche Bank FXSelect platform and collected information about 42 managers' activities from November 2004 to May 2009. To explain a manager's return on a time-varied basis they used a moving window regression approach, where one of the factors is the expected return on a certain currency. The authors built an estimator with the use of a covariance matrix of returns with higher weighting allocated to currency pairs where the correlation of returns is high as well as to currencies with riskier returns.

Using a similar dataset, Pojarliev and Levich (2011) estimated currency investors' performance to find out if their trading behaviour is similar with one another. They also used the database from Deutsche Bank FXSelect platform of hedge funds' returns from April 6, 2005, until June 30, 2010. The authors measured the total return as a regression with such factors as a measure of active manager skill, a systematic risk premium in the market, the sensitivity of the manager's returns to the factor and a random error term. The model showed between 50% and 75% variability in currency fund returns. It was also observed that strong and weak performers remain consistent over 2-3 year horizons. The authors also applied this model to currency volatility in relation to professional currency managers and found that currency volatility is a significant causal factor.

In general, the literature on institutional forecasters and traders in the FX market shows that these entities exhibit heterogeneity in performance, and that persistence exists in both top and bottom performers. This may suggest that some institutional entities possess different private information and use different proprietary models which leads them to varying market expectations.

2.2.5 Evidence on Futures Traders

One prominent study in the futures markets was conducted by Hartzmark (1991), who investigated traders' skills to predict price movements in futures markets, and argued that profitability is the result of luck. The author used data from July 1977 to December 1981 from the Commodity Futures Trading Commission (CFTC) for the following markets: Chicago Board of Trade (oats, wheat, U.S. T-bonds), Minneapolis Grain Exchange (wheat), Kansas City Board of Trade

(wheat), Chicago Mercantile Exchange (pork bellies, live cattle, feeder cattle), and International Monetary Market (90-day T-Bills). The author categorised traders as “Pure hedgers” (commercial traders), “pure speculators” (non-commercial), and those who report both kinds of positions. Only traders who made at least 25 transactions (purchases or sales) were included in the study. The author developed the Big Hit Ability (BHA) measure to examine traders’ ability to increase their position whenever the market moved favourably with a significant change. Hartzmark stated that trading in the futures market is statistically analogous to a coin toss where positive and negative outcomes are determined by luck. In other words, returns are generated by a stochastic process. The author showed that there is no significant relationship between dollar returns and forecasting coefficients. Moreover, the distribution of the BHA measure was found to be positively skewed: all seven observed markets were uniformly distributed for commercial traders and five out of seven markets were uniformly distributed for non-commercial traders. The only market where forecasting ability was significant and positive was the oat market where the results were dominated by traders with significantly large-volume positions. The author concluded that private information could be the reason for the high level of BHA. Moreover, while commercial investors showed better forecasting abilities compared to non-commercial investors, their returns still depended on luck.

Similarly, Leuthold et al. (1994) also applied the BHA measure in the futures market to examine the frozen pork bellies traded on the Chicago Mercantile Exchange over a 9-year period (1982-1990). The sample contained 3,171 traders with over 450,000 daily trading observations. The authors used the rate of return

to calculate investors' performance, and measured the BHA of the observed traders. The results showed that investors had a very strong ability to forecast and make a big hit (forty profitable agents compared to eighteen losers), and the forecast coefficients showed a significant relation to the profitability, especially for speculators and short hedgers.

Egelkraut et al. (2007) also used the BHA measure of Hartzmark (1991) to investigate whether investors can predict price volatility changes in the corn options market. The authors used data provided by the Chicago Board of Trade on corn options settlement prices on contracts from 2 January 1987 to 31 December 2001, and daily corn futures settlement prices from 17 February 1984 to 22 November 2002. Their results showed that early-year options predict the direction and change of realised volatility, unlike the later-year options.

The success ratio was used by Alquist and Kilian (2010) to measure the extent to which oil futures can estimate future market prices. The dataset contained daily prices of crude oil futures from NYMEX from March 1983 to February 2007. The authors defined the success ratio as the fraction of forecasts that correctly predicted turning points in the price of oil, based on the success ratio statistic of Pesaran and Timmermann (1992). Their results showed that the predictions were only correct at the 9-month and 12-month horizons.

Fishe and Smith (2012) identified informed traders in futures markets using the success ratio and used data from the Large Trader Reporting System (LTRS), which is maintained by the CFTC and included the trades of 8,921 traders in 12 commodity markets (corn, soybeans, wheat, copper, gold, silver, WTI crude oil, heating oil, natural gas, cotton, soybean oil and sugar futures contracts) from

January 2000 to May 2009. The authors used a binary measure of success and identified only a small percentage of traders as overnight informed or daily informed. Moreover, the authors found significant predictive power for various trader characteristics such as trading experience, position size, trading frequency and type of positions.

The evidence in the futures market mainly suggests that it is not skill, but rather luck which results in some trader exhibiting positive excess performance. One may argue that the futures market is mainly commodity-based where there is little fundamental information about the underlying asset, which is mainly driven by forces of supply and demand. As such, private information to generate positive excess returns may not be available in the futures market, which implies that the performance of top traders in this market is not due to skill but rather to luck.

2.2.6 Evidence on Stock Traders

Following the earlier argument that there is not much opportunity to gather significant private information in the futures market, I review the evidence provided in the stock market, where it is possible to obtain fundamental information about the stock being traded through in-depth company research. In an early study, Ross (1975) defined winning traders as those who recorded a profit after deducting commissions over the entire life of the account. The author investigated two groups of investors of a large commodity trading house. After fees had been deducted from profits, the majority of both groups of traders incurred losses. Losses were the highest during the first two years, and there was no evidence of improved performance after accounting for trading experience.

Traders have the tendency to become addicted to speculation and deposit more funds even if they continue to lose. Ross concluded that many investors lack the background necessary to be successful and rely heavily on their brokers — which further highlights the importance of choosing a suitable broker. Hence, the research obtained from the broker adds value to the trader, rather than the trader adding value through skill.

Nicolosi et al. (2009) examined traders' ability to forecast both the direction and magnitude of future excess stock returns. The sample contained 78,000 households from January 1991 to December 1996, including information about end-of-month portfolio positions, all trades (common stocks, options, and other securities) and investor characteristics files (age, income, etc.). The authors analysed retail investors' stock trades and showed that individual investors learn from their trading experience. They defined forecasting ability to be the percentage of previous trades that were profitable overall. Their results showed that stock selection ability significantly affects stock purchases, with the exception of short-term (5 trading days) forecasts. The evidence suggests that individual stock investors do learn and adjust their behaviour effectively, thus improving investment performance over time.

Similarly, Griffin et al. (2012) investigated private information at the broker level. The data used consisted of brokerage houses trading NASDAQ-listed firms from January 2, 1997 to December 31, 2002, and included date, time, ticker symbol, trade size, the price of each transaction for each stock and market maker IDs from the settlement process. To identify successful brokers, the authors used the success ratio, defined as the percentage of imbalances in the right direction for

the identification of those clients. They found that some investors gain profits in the twenty-day period prior to earnings announcements. However, it was undetermined whether their trading decisions and performance were based on private or public information. They concluded there is no evidence to identify brokerage-level trading patterns of information leakage to favoured clients.

The evidence from equity traders shows that information can give traders an advantage to generate excess positive returns. This is in contrast to the general findings in the futures markets where positive returns are attributed to luck rather than skill. This argument raises the question of whether positive performance in the FX market is due to luck since there is very infrequent fundamental news announcements by central banks and governments compared to earnings and company news announcements in the equities market. While the FX market is driven to a certain extent by macroeconomic factors such as interest rates and government policies, the overall price dynamics of this market have been characterised as a random walk (Hayley and Marsh 2016). Nevertheless, savvy traders may be able to gauge some of the fundamental directional movements of the market based on expectations of how governments and central banks will change their policies. Such qualitative data has become available and easily accessible in the form of surveys and polls from news agencies and even through social media. Hence, there should exist potential opportunities to generate positive excess returns from fundamental information in the FX market, and it is up to the individual trader to gather, analyse, and correctly interpret the news in order to make an informed trading decision.

2.2.7 A Note on Skill vs. Luck

Distinguishing between skill or luck is one of the most debated topic in financial literature, especially regarding mutual fund and hedge fund managers. Such distinction is important from a forward-looking decision-making perspective because skill is generally permanent while luck is random by definition. An investor who was skilled during the last period will most likely be skilled in the future period, while an investor who was lucky last period is no more likely to be lucky again than any other investor in future periods.

While arguing that the separation of skill and luck is an important task, actually doing so is a very challenging endeavour since skill and luck are not independently observable (Cornell, 2009). Nevertheless, skill has been strongly associated with performance, and the latter can be measured using a variety of techniques and metric. However, depending on the performance measure that is used, the conclusion about skill can vary significantly. The performance measures that will be used in this thesis will be discussed in greater detail in the methodology section, but I present two of them here in order to highlight the difficulty and subjectivity behind assessing an individual's skill.

Two of the measures that I will use are the success rate (SR) of a trader, which is simply the proportion of successful trades, and the return on investment (ROI), which captures the profit generated in relation to the balance of the trader. Suppose a trader executes nine profitable trades, each with a profit of one dollar, and one unprofitable trade with a loss of ten dollar. If we compute the SR of the trader we obtain a 90% rate, which signifies an ability to predict the direction of

future price movements. However, when we compute the ROI of the trader, we obtain a negative number which means that the trader is unable to add value in absolute terms to their initial wealth. As such, the SR suggests that the trader has skill while the ROI implies otherwise. Another argument is that the trader may indeed possess the skill to predict future price movements and add value in dollar terms when considering the first nine trades, but may lack the proper risk management skills to hedge against extreme adverse price swings. This shows that there are many different types of skills, each of which is valuable in regards to generating and preserving wealth.

This discussion emphasises the point that there are many different types of skills and measuring them is a very difficult task. In this thesis, I specifically test for three performance-based skills which are 1) a trader's ability to correctly predict future price changes, 2) a trader's ability to add value in absolute terms to an initial investment, and 3) a trader's ability to profitably adjust their position size based on their expectation of the magnitude of price movements.

2.3 Market Volatility

2.3.1 Market Participation and Volatility

The relationship between the level of trader participation and exchange rate volatility was examined by Hau (1998) using data on trading profits sourced from twenty large U.S. banks, and showed that higher trader participation increases exchange rate volatility (Ito et al., 1998). The author developed a dynamic model of endogenous traders subject to heterogeneous expectations and found that expectation errors create excessive market entry and excess volatility. Specifically, marginal trader entry in the market has two effects: 1) “it increases the capacity of the market to absorb exogenous supply risk” and 2) “it adds noise and endogenous trading risk”. In the case of a positive tax on margin traders, participation and volatility decreases alongside an increase in market efficiency. The model suggests additional market implications such as an explanation for exchange rate heteroscedasticity and a positive correlation between volatility and trading profits. High information content of the market price translates into negative information externality that dominates risk sharing benefits.

Similarly, Bauwens et al. (2006) presented evidence that does not support the hypothesis that an increase in the number of traders reduces volatility. The authors investigated the relationship between volatility and other market determinants (central bank policy, the number of information events, etc.), using Norwegian weekly exchange rate volatility figures from 1993 to 2003. The authors used distribution hypothesis (MDH) to prove that investors may purchase

currencies even when volatility is elevated, which indicates their high-risk tolerance/appetite.

The evidence presented above implies that volatility in popular markets, such as the EUR/USD, should be no different than the volatility in other exotic currency pairs. One reason for this may be due to FX markets being interrelated as contended by interest rate parity theory. It follows that an increase in volatility in one currency will spill over into other currencies since the flows in and out of one currency will be channelled into others. This implies that we can expect similar volatility-performance relationships across currencies that have similar characteristics, including liquidity and spreads to name a few. Nevertheless, liquidity is often sparse and spreads are wider in exotic pairs, which means that, while volatility may spill over into these exotic currencies, the magnitude and effect of the volatility may be more complex to estimate especially during times of market turbulence.

2.3.2 Trader Expectations and Volatility

Hau (1998) distinguished between financial institutions and traders. The author described financial institutions as rational venues that make critical decisions regarding which traders to hire to undertake trading activities on their behalf. On the one hand, traders' profitability is influenced by past and current exchange rates — they have imperfect trading abilities due to temporary expectational errors related to the excess return, which can deviate from the optimal currency demand. On the other hand, financial institutions can make optimal hiring decisions based on rational expectations about the traders' imperfect trading

abilities. The author found a positive relationship among trading profits and volatility for financial institutions, and a limited forecasting ability among traders. This means that if the expected profits are too low relative to the level of financial risk, financial institutions will not enter the market. After investigating expected excess returns, price volatility and investors' demand, the author concluded that under high volatility, risk-averse agents naturally reduce their demand since it is more difficult to make predictions and remain profitable.

Carlson and Osler (2000) investigated the microstructural connection between rational speculative activity and exchange rate volatility by distinguishing between two types of agents: 1) informed or rational speculators and 2) the current account traders who can be interpreted as importers and exporters of goods and services. In addition, the authors considered two types of market shocks: 1) those that do not affect speculators' preferred portfolio positions directly (like changes in liquidity demand), and 2) those that bring direct influence, such as changes in interest rates. Regarding the latter type of market shock, the authors showed that speculators do not play a stabilising role due to the fact that conditional variance amongst exchange rates monotonically increases with the amount of speculation activity. The authors also modelled the speculators' constant absolute risk aversion utility function, which reflects their desire to take a bet each period for a certain amount of profits, and the welfare function, which reflects speculators' expected utility, in order to identify the desired target portfolio. Risk premium of the speculators depends on risk aversion, the outstanding stock of foreign currency and the exchange rate's conditional variability. In summary, the exchange rate's variance causes speculators to adjust their bet coefficients.

Jeanne and Rose (2002) also investigated volatility in the foreign exchange market using monthly data obtained from the Financial Times Currency Forecaster for thirteen different (dollar) exchange rates from 1996 to 1999. They found that exchange rate volatility may include a non-fundamental component: noise trading that is based on whims, fads and non-fundamental influences (Jeanne and Rose 2002, p. 2). The authors further examined the reasons behind noise traders' decisions to enter the currency markets, and argued that noise traders have two counteracting roles: 1) to create risk and 2) to share risk. The authors developed a conventional monetary model of the exchange rate with flexible prices to calculate the price of foreign exchange rates by assuming that investors are risk averse and that they will not enter into currency transactions if the exchange rate is stochastic. Investors were modelled to have the same endowments and tastes, but with different levels of trading ability. Some of them were able to form accurate expectations on risk and returns, while other had noisy expectations with associated entry costs. Traders decisions to enter the market, the portfolio allocation problem and the end-of-life wealth of each trader were modelled. Since noise traders have imperfect knowledge of the determinants of the exchange rates, their activities are expected to increase volatility. In addition, the authors found that exchange rate variance tends to raise the risk premium, and at the same time, increases the total number of investors demanding domestic currency, which lowers the risk premium (non-monotonic influence). As for the influence of volatility on traders, trade volume is higher with floating exchange rates. This means that agents tend to trade more following higher returns. Similarly, Shi and Xu (2009) expanded on the work of Jeanne and Rose (2002) by proposing a model incorporating noise traders with noisy expectations

and informed traders with rational expectations, where both categories of individuals must pay an entry cost to trade in the foreign exchange market. Noise traders may create big fluctuations and because of that, informed agents build their expectations about excess returns, considering the relative presence of noise traders in the market. As for investors' behaviour, their decision to enter the market is based on the time of market shocks, the expected returns and the future exchange rate.

In a more recent study, Skoupil (2015) examined the behaviour patterns of foreign exchange hedgers, whose aim is to minimise FX market risk. The author defined hedging activity as "managing market risk in a way that both the risk and the costs caused by the hedging are in approximate balance" (Skoupil 2015, p. 512). Since the level of volatility is a very deterministic feature in the foreign exchange market, hedgers have to pay strong attention to its ever-changing rate. Hedgers cannot be consistently profitable since they are not sufficiently informative, therefore they try to minimise their exposure (volatility of profit and loss) to FX market risk while maintaining the necessary part of the business activity in denominated foreign currencies. Using EUR/USD exchange rates from January 2010 to February 2015, the author calculated 1) the sum of expected positive and negative cash flows in the foreign currency, 2) the value contracts that are already concluded at a fixed price and volume, and 3) contracts that are expected to happen based on the available information. The study concluded that if hedgers want to decrease the volatility of profit and loss, they need to decrease the level of exposure to foreign exchange rate volatility.

In a related study, Corte et al. (2016) examined the relationship between return and volatility predictions by creating a currency strategy to predict the currency volatility risk premium (VRP) for changes in spot exchange rates (i.e. the difference between expected future realised currency volatility and a model-free measure of implied volatility derived from currency options). The mechanics of the VRP strategy are the following: the strategy buys currency with a relatively cheap volatility insurance (highest volatility risk premium quintile) and sells currencies with expensive volatility insurance (lowest volatility risk premium quintile). This mechanism can be defined as the cost of insurance against volatility fluctuations in the underlying currency. The authors studied how the latter can affect currency returns predictions and thus investors decisions to form their portfolios. They concluded that there is a mutual relationship between volatility and traders' behaviour. For example, as the well-informed and wealthy investors start trading, the fluctuations may become significant, which goes on to affect other agents forming or changing their expectations about future volatility and expected returns. Many market participants are found to increase their trading volume in response to abnormal profits. However, when volatility reaches a certain point, investors tend to reduce their purchases to avoid significant losses. Thus, the main findings are that: 1) there exists an intention to generate more profits while volatility is high, and 2) agents build and apply different expectation models to predict those fluctuations.

All evidence presented in the literature supports a positive relation between market volatility and trader participation in the FX market. The reason is that heightened market volatility produces large price swings which traders deem

highly potentially profitable. Nevertheless, high volatility can also be detrimental to performance, especially for highly leveraged positions. As such, I expect that the higher the market volatility, the less the trader is able to gauge the direction of the market, and the less the individual is able to demonstrate their skill. In other words, heightened levels of volatility will negatively impact a trader's skill and performance.

2.3.3 Volume and Volatility

Hagiwara and Herce (1999) examined how exchange rate volatility influences investors' portfolio and trading volume. They used data from Harris Banks, in details a one-month Euro-currency rate for Canada, United States (US), United Kingdom (UK), France, Belgium, Germany, the Netherlands, Italy, Switzerland, and Japan, having also the spot exchange rates for the Canadian dollar, Belgium franc, British pound, German mark, French franc, Italian lira, Dutch guilder, Swiss franc, and Japanese yen to test their models' efficiency (971 observations from 1 June 1973 to 3 January 1992, except for the EUR-YEN rate). The authors developed two models: 1) a model of portfolio choice, where the volatility of real exchange rate was used and 2) a model that highlighted the relationship between trading volume and volatility. The authors found that different patterns of the relationship between volume and price variability emerge depending on the distribution of endowments and when the distribution of these endowments is symmetric, the correlation between volatility and trading volume is positive, and vice versa for asymmetric endowments.

The relation among volatility, trading volume and spreads was also studied by Galati (2000), who found that volatility and bid-ask spreads are positively correlated. Trading volume is found to have a positive correlation to volatility, but only during periods of stable volatility, while a negative correlation is found when volatility increases sharply. The author used data from the Central Bank Survey of Foreign Exchange and Derivatives Market Activity and the Chicago Mercantile Exchange related to the Mexican peso, the Colombian peso, the Indian rupee, the Brazilian real, the Indonesian rupiah, the Israeli shekel and the South African rand-dollar exchange rates from January 1998 to June 1999. Firstly, the author measured the volatility and trading volume behaviour during normal trading periods, as well as the correlation for all the currencies used. In summary, traders tend to be more risk-aggressive when the market endures heavy fluctuations; however, when volatility becomes too strong, they tend to reduce trading volume due to trading limits reaching their pre-determined risk tolerance limits.

Bjornes et al. (2002) studied the impact of volume on volatility in the FX market and found a positive correlation with volatility and trading volume in the Swedish krona (SEK) market (SEK/EUR exchange rate movements from January 1, 1993 to December 31, 2001). The sample used was primarily dominated by commercial banks. The authors connected heterogeneity in expectations found among institutional investors and the level of volatility in the FX market. This showed that trading volume is concentrated around the largest banks during periods of high volatility.

In an earlier study, Tse and Tsui (1997) investigated the relationship between heterogeneous expectations and volatility in the Malaysian and Singaporean

foreign exchange markets. Using 4,067 daily closing spot exchange rates of the Malaysian ringgit-US dollar and Singapore dollar-US dollar from 3 January 1978 to 29 June 1994, the authors showed that persistence in volatility is mainly due to heterogeneous expectations. Moreover, in reaction to exchange shocks, trading occurs to resolve heterogeneous assumptions. Also, the asymmetric effects of foreign exchange shocks on future volatility may be due to the unbalanced reaction of expectations to such shocks (heterogeneous expectations hypothesis).

Aggarwal and Mougoue (2011) also studied the relationship between volatility and trading volumes by analysing historical prices for the British pound, the Canadian dollar, the Japanese yen and futures contracts from the Futures Industry Institute (December 1, 1978 - August 21, 2009 for the Canadian Dollar, November 1, 1977 - August 21, 2009 for the British Pound, and November 21, 1978 to August 21, 2009 for the Japanese Yen). The authors tested for linear and non-linear time trends in trading volume and found that there is a correlation between trading volume and linear/quadratic time trends. Moreover, the authors used the generalised method of moments (GMM) approach to investigate the relationship between return volatility and trading volume. The results showed that there are significant lead-lag relations between trading volumes and return volatility, which means market fluctuations have a strong influence on investors' decisions to purchase currencies.

In general, the literature shows that heightened market volatility is partly driven by heterogeneous expectations. Moreover, when volatility is high, volume tends to decrease as traders reach their position limit and risk appetite. This suggests that

traders change their behaviour depending on the current market conditions. In other words, traders alter their trading decisions by changing their position size in response to changing market conditions.

2.3.4 News and Volatility

Hua and Gau (2006) studied the intraday Taiwan dollar/U.S. dollar (NTD/USD) exchange rate patterns by applying a GARCH model to identify the cyclic seasonality in the intraday volatility of the NTD/USD exchange rate. The Bloomberg Professional Service was used to obtain public news announcements in Taiwan and the U.S. at 15-minute intervals from January 4, 2001 to December 31, 2001. The Taipei Foreign Exchange Brokerage Inc. was used to obtain data for the NTD/USD spot exchange rates and trading volumes at 15-minute intervals. The results showed a significant relationship among volatility, news and traders adjusting their inventory positions. Specifically, as Taiwan's news was made public at the opening of the market, traders adjusted their inventory positions due to the risk created from US dollar depreciation, which caused a higher level of volatility in its own right within the NTD/USD exchange rate, and consequently led to further central bank interventions.

Goddard et al. (2015) investigated the relationship between FX market volatility and investors' active attention, measured by a Google search volume index (SVI). The authors used weekly data from January 2004 to September 2011 for seven currency pairs: GBP/USD, USD/JPY, EUR/USD, USD/AUD, EUR/JPY, EUR/GBP, and GBP/JPY, accounting for more than 69% of the total turnover in FX markets in 2004, and found a positive and significant relation between SVI

and risk aversion (the difference between option implied volatility and realised volatility). Moreover, the authors showed that changes in SVI are positively correlated with the changes in trading volume. Investor attention is strongly associated with changes in trading volume among the largest traders in the FX market (banks) and there was a significant connection between attention and volatility. Investor attention is found to contain predictive information regarding the volatility of future currency returns, even after controlling for news supply and macroeconomic uncertainty. Hence, investor attention is also associated with time-varying risk aversion measured by the variance risk premium.

Marshall et al. (2012) examined the impact of news announcements on foreign exchange implied volatility (IV) using data on daily IV of 1-month at-the-money options on four major FX pairs (USD/EUR, USD/GBP, USD/CHF and USD/JPY) obtained from Olsen and Associates. The authors showed that for US scheduled macroeconomic news announcements, the FX IV tends to drop on the day of the announcement, but there were no significant changes found in FX IV levels pre- and post-announcements. Moreover, larger announcement surprises can in some cases influence FX IV differently compared to smaller surprises, and the magnitude of the impact of positive news is generally not different to that of negative news. Regarding the three other types of announcements: 1) minutes of the Federal Open Market Committee (FOMC), 2) official US interest rate changes and 3) Bank of Japan (BOJ) interventions, the only impact on the FX IV was found for BOJ interventions indicating that these interventions result in upward revisions in expected future market volatility.

Similarly, Evans and Speight (2010) examined the relation between macroeconomic announcements and intraday euro exchange rate volatility. They used inter-bank bid-ask quotes for Euro-Dollar (EUR-USD), Euro-Sterling (EUR-GBP) and Euro-Yen (EUR-JPY) spot exchange rates provided by Olsen Data from January 2002 to July 2003. The authors found that macroeconomic news announcements from the US cause the majority of statistically significant changes in volatility, with US monetary policy events and real activity announcements causing the largest volatility changes across the three exchange rates.

As mentioned earlier, fundamental news announcements in the FX market are followed by many traders and have the potential to significantly impact exchange rates. Those who are able to use fundamental data and form correct predictions prior to announcements on a consistent basis are likely to possess genuine trading skill.

2.3.5 Impact of Volatility on Trader Performance

Olson (2004) and Qi and Wu (2006) found evidence of declining trading profits over time. The authors argued that moving average trading rules do not generate large abnormal returns as they did previously in the 1990s. They explained this phenomenon through the notion that the foreign exchange market is becoming more efficient, meaning fluctuations are caused by fundamental information, rather than the activities of noise traders.

Cornell and Dietrich (1978), Dooley and Shafer (1984), Lee and Mathur (1996) and Neely and Weller (1999) proposed that technical trading rules are more

profitable for currencies experiencing relatively higher volatility. Specifically, Cornell and Dietrich (1978) examined whether the foreign exchange market is efficient. The authors used the same data as Dooley and Shafer (1984) from the New York Federal Reserve Bank as well as the Standard and Poor's 500 index, and they applied different trading rules: the filter rule (Alexander, 1961), moving average rule and Praetz (1976) tests. The results showed that from the investigated currencies, the franc mark and guilder showed the highest returns with the largest variance in daily rates of return, thereby indicating the existence of a positive correlation between volatility and traders' performance. Dooley and Shafer (1984) also found that exchange rate patterns reflected relative returns from different currencies using daily foreign exchange rate series. The authors stated that potential windfall wins and losses can exist only as a result of high volatility.

Bilson (1980) investigated whether there were any opportunities for abnormal profits for speculative traders participating in the FX market. Using the movements of five major currency pairs from January 17, 1975 to November 14, 1980, Bilson found a positive correlation between exchange rate volatility and the level of speculative trading gains, which suggests that as markets become more stable, speculators become less profitable. This finding opposed earlier evidence presented by Telser (1959).

Lee and Mathur (1996) tested the moving average (MA) trading rule for six European spot cross-rates using daily closing spot or cash prices on European cross-rates from May 23, 1988 to December 31, 1993, supplied by the Knight-Ridder Database. They found that the Japanese yen/Deutsche mark and the

Swiss franc/Deutsche mark had significantly positive returns parallel to high volatility rates.

Kho (1996) analysed the role of time-varying risk premia and volatility in explaining technical trading rule benefits. The author used moving average crossover rules to examine the British pound (BP), Japanese yen (JY), Deutsche mark (DM), and Swiss franc (SF) futures contracts patterns from the International Monetary Market (IMM) division of the Chicago Mercantile Exchange for the period from January 1980 to December 1991. The study concluded that 10% of generated profits could be explained by volatility in the observed time-period.

Bollerslev and Melvin (1994) studied the relationship between the magnitude of foreign exchange market spreads and underlying exchange rate volatility, using more than 300,000 continuously recorded Deutsche mark/dollar quotes from April 1989 to June 1989. The empirical results indicated a strong positive correlation between volatility and market spreads.

Neely and Weller (1999) found that the reduction in volatility may reduce trading profitability. Using half-hourly bid and ask quotes for spot foreign exchange rates during 1996, obtained from the HFDF96 dataset provided by Olsen and Associates, the authors found that low volatility coupled with the effect of transaction costs leads to economically insignificant excess returns; and since the Dutch guilder had the lowest variability against the German mark, it was the only observed currency that did not generate significant profits. Contrary results were found with the Italian lira, which had the highest variability of all currencies during the examined period.

Pojarliev and Levich (2011) criticised the carry trading strategy, showing that between April 2005 and March 2008, carry trading showed an essentially zero return and was negatively correlated with volatility. The authors used a four-factor model to analyse the profitability of 107 currency managers who are part of the Deutsche Bank (DB) FXSelect platform. The results showed that different types of investors generate different returns due to volatility. For instance, so-called “dead” managers (those who exited the platform due to poor performance) generated lower profits when fluctuations increased. This illustrates the impact of volatility on a trader’s life span in retail foreign exchange markets. In general, 2 out of 15 managers were able to benefit from falling volatility, and 2 investors made profits from rising volatility.

Abbey and Doukas (2015) researched individual currency traders’ activities. The dataset comprised account data from an online advisory service obtained from Collective2.com including individual retail spot currency traders. They used a modified four-factor model, originally developed by Pojarliev and Levich (2010) to calculate the daily returns of an equally weighted portfolio where volatility was a chosen factor, because carry traders trade on currency volatility alongside carry trading, momentum-following and value factors.

The literature shows that volatility can create profitable trading opportunities; however, heightened volatility can have a detrimental effect on a trader’s wealth if it is not properly accounted for and mitigated.

2.4 The Effect of Behavioural Biases on Performance and Skill

In this section, I review the literature related to five popular behavioural biases that help shape traders' behaviour, and consequently, affect their performance. In what follows, I discuss five of the most popular behavioural factors that have been reviewed in previous literature.

2.4.1 Herd Initiations

In the literature, 'herding behaviour' or simply, herd behaviour, is defined as the tendency for individuals to ignore private information in favour of majority-held popular opinion (Scharfstein and Stein, 1990; Bikhchandani et al., 1992; Banerjee, 1992; Avery and Zemsky, 1998). Bikhchandani and Sharma (2000) characterised herding behaviour into two types: intentional (true) herding and unintentional (spurious) herding. Intentional herding occurs when individuals willingly decide to ignore their private information and follow the popular opinion of other market participants because they expect that others possess superior private information. Unintentional herding arises due to individuals trading on common information or using the same models to forecast and trade. While unintentional herding is a logical outcome of an efficient market because information is quickly acted upon by individuals and absorbed into market prices (Sias et al., 2001), intentional herding can increase market volatility and destabilise markets as trades become highly correlated (Scharfstein and Stein 1990, Hirshleifer and Teoh 2003, and Hwang and Salmon 2004). Distinguishing between these two types of herding is very difficult, since it is conditional upon identifying the intent of the trader.

Intentional herding can be further divided into rational and irrational. Rational herding occurs when traders decide to imitate the trades of another individual deemed to possess superior market information and who typically has a proven track record of success. On the other hand, irrational herding behaviour occurs when individuals decide to ignore their own private information in favour of simply following the majority in order to avoid the regret associated with underperforming their peers (Devenow and Welsch 1996, Nofsinger and Sias 1999, Sias et al., 2001).

2.4.1.1 Drivers of Herding Behaviour

Many studies have investigated the drivers behind herding behaviour. I summarise the most common drivers below:

2.4.1.1.1 Preservation of Reputation and Compensation

Researchers including Scharfstein and Stein (1990), Trueman (1994), Zwiebel (1995), Prendergast and Stole (1996), Graham (1999) Chevalier and Ellison (1999), Holmes et al. (2013), and Jiao and Ye (2014) have argued and found evidence showing that fund managers, as noted above, herd in order to preserve their reputation and avoid the regret associated with underperforming their peers. As such, fund managers are likely to ignore their own private information and follow the herd in order to avoid potentially underperforming the benchmark, especially since their compensation is directly related to their performance relative to a benchmark. Consequently, higher herding levels are typically observed among more experienced fund managers. Herding behaviour to

preserve reputation also extends to the opinions of investment analysts and newsletters (Hong et al., 2000).

2.4.1.1.2 Information Availability

The availability of information related to the asset being traded is a significant driver of herding behaviour. Studies including Lakonishok et al. (1992), Lin et al. (2007), Choi and Sias (2009), and Venezia et al. (2011) have presented significant evidence of higher herding levels in small-cap stocks relative to big-cap stocks. The authors determined that the reason behind higher herding in small-cap stocks is due to the limited, or lower amount, of information available to investors regarding these stocks. Hence, when market information is scarce, investors look at each other's activities as a source of valuable information in order to gauge the direction of the market. Similar evidence was reported by Diamond and Verrecchia (1991), who found that when information asymmetry increases, market liquidity declines, and herding behaviour increases. Bikhchandani and Sharma (2000) identified this phenomenon as herding due to information cascades. Information cascades can easily change the course of herding behaviour, and investors choose either to invest in the cascade or stay out of it. For example, Ederington and Lee (1993), Bollerslev et al. (2000), Nikkinen and Sahlström (2004) and Galariotis et al. (2015) found that in the US, herding increases when price-sensitive macroeconomic news is published. Chang et al. (2000) found similar evidence in the South Korean and Taiwanese markets, respectively.

Park and Sabourian (2011) developed a standard sequential security trading model and argued that individuals herd only in cases where their information is

sufficiently dispersed, such that, they consider extreme outcomes more likely than moderate ones. Similarly, traders follow a contrarian strategy only if their information drives them to focus on middle values. In general, both herding and contrarianism produce excess price volatility and lower liquidity.

2.4.1.1.3 Market Conditions

Researchers have investigated herding behaviour in relation to different market states; however, the arguments in the literature are mixed.

Chiang and Zheng (2010), Klein (2013), Messis and Zapranis (2014), Mobarek et al. (2014), and Ramli et al. (2016) found that herding behaviour increases during times of crises and market instability. The reason is that when markets are highly volatile and unstable, individuals panic and look at what others are doing in the hope of obtaining potentially valuable information about the direction of the market. Thus, individuals have lower confidence in their own private information during times of crises and choose to simply follow the herd. Similarly, during market bubbles, investors ignore analyses of the market and decide to “ride the wave” as others are doing in the hope of profiting from the market momentum.

Empirical evidence has been found in several markets including the Chinese (Hu, 1999; Mei et al., 2004; Demirer and Kutan, 2006; Tan et al., 2008; Chiang et al., 2010), Taiwanese (Demirer et al., 2010), US and UK (Galarioti et al., 2015), Arab Gulf (Balcilar et al., 2013), South Korean and Japanese (Chang et al., 2000), Hong Kong (Zhou and Lai, 2009), Poland, (Goodfellow et al., 2009), Greece and other South European markets (Caporale et al., 2008; Economou et al., 2011).

Moreover, herding can arise simply due to diversification, from one asset class into another, or between countries. Ramli et al. (2016) examined herding behaviour in the Indonesian market during the financial crisis of 2008 and found that foreign investors in the Indonesian market — specifically those from the U.S or Europe, who wanted to benefit from the low correlation between their home portfolio and the Indonesian market, were likely to herd with domestic investors due to their lack of knowledge of the new market.

On the other hand, some studies have shown that while herding is high during market crises, this behaviour is caused mostly due to the selling desire of investors who wish to limit their losses (Boortz et al., 2013). In other words, the dominant selling behaviour is not due to investors looking at each other's actions, but rather in view of their own preference to limit their loss. Supporting evidence is provided by Kremer and Nautz (2013) who found that sell-herding arises when there is a reversal in asset returns.

2.4.1.1.4 Feedback Trading

A similar driver affecting herding behaviour is feedback trading. Positive feedback trading is a strategy where traders buy assets that have recently risen in value and sell assets that have fallen in value, while negative feedback trading is a contrarian strategy where traders buy assets that have recently decreased in value and vice versa. Lakonishok et al. (1992) argued that institutional investors herd unintentionally in cases where their trading decisions are based on common fundamental information. In addition, herding among institutional investors can also arise when these institutions decide to trade against irrational behaviour in the market, thus following a negative feedback trading strategy. Hence, following

a similar trading strategy can exhibit herding behaviour when examining a specific group of investors. Herding which arises from feedback trading, while unintentional, can destabilise financial markets since decisions are not based on fundamentals, but rather on the momentum of the market (De Long et al., 1990b).

2.4.1.2 Empirical Evidence on Herding Behaviour

2.4.1.2.1 Herding in Equity Markets

Estimating herding behaviour means examining an individual's tendency to buy or sell an asset at the same time as other participants, relative to what would be expected if these individuals traded independently (Lakonishok et al., 1992). Many studies including Sias et al. (2001), Barber et al. (2009) and Chiang and Zheng (2010) distinguished between a static (cross-sectional) and a dynamic (time-series) herding estimation, where the former measures herding that is happening within a specific period while the latter measures herding across different trading periods.

Christie and Huang (1995) developed two cross-sectional methods to detect and estimate herding behaviour in periods of huge upward or downward trends in stock markets. The first is called the cross-sectional standard deviation (CSSD) and the second is called the cross-sectional absolute deviation (CSAD), where the CSAD is not affected by outliers. When investors herd, the dispersion around the market consensus is expected to be low. The results for both daily and monthly returns are not consistent with the existence of herding behaviour during times of large price swings. This means that during severely declining markets, in which herding behaviour is expected to be very high, the magnitude of the

increase in dispersion of actual returns, is reflected by the increase in dispersion of predicted returns, which are estimated using rational asset pricing models.

Chang et al. (2000) proposed another variation of the CSAD using the entire distribution of financial market returns. The correlation between the observed stock return of the firm and the CSAD was used to detect herding behaviour. The authors found no evidence of herding in the US and Hong Kong markets, partial evidence of herding in the Japanese market, and significant evidence in the South Korean and Taiwanese markets.

Hwang and Salmon (2004) proposed an alternative method for estimating herding based on the cross-sectional dispersion of the factor sensitivity of assets within the market. It enables the detection of herding within a particular sector or towards a certain trading style. By doing so, one can distinguish true herding behaviour from expected movements in asset returns that are driven by fundamentals. Using data on both U.S and South Korean stock markets, the authors found that herding is significant, once general market conditions and macro factors have been taken into account.

Demirer et al. (2010) use firm-level data in the Taiwanese stock market, to find that the linear model based on CSSD shows no significant evidence of herding among Taiwanese investors. Nevertheless, the non-linear model proposed by Chang et al. (2000) and the state space models developed by Hwang and Salmon (2004) show significant and consistent evidence of herding behaviour in all sectors. Moreover, the authors found that herding is more pronounced during downward moving markets.

Jiao and Ye (2014) and Andreu et al. (2015) analysed herding behaviour in the style exposures of mutual funds and concluded that mutual funds usually follow hedge funds, and the level of herding increases with performance. The authors also found that hedge funds almost never follow mutual funds. In an earlier study, Kaminsky et al. (2004) found that mutual funds exhibit herding behaviour in Latin America, where the main source of herding was the news from other emerging markets.

Galariotis et al. (2015) used macroeconomic variables to explain the herding behaviour in leading US and UK stocks. The authors showed that US investors are more likely to herd when important macro news is released and that there was a herd spill-over effect from the US to the UK during previous financial crises. Moreover, they found that US investors herd based on both fundamental and non-fundamental information during different crises, while UK investors only herd due to fundamentals, or during the first 'Dotcom' bubble crisis. These findings indicate that the factors driving herd behaviour are both period and country specific.

2.4.1.2.2 Herding in the FX market

Carpenter and Wang (2007) investigated the effect of private information on herding behaviour. Using the herding measure proposed by Lakonishok et al. (1992), the authors found a significant impact from herding on prices in the USD/AUD market, and concluded that herding generates greater effects on market prices, especially when behaviour is initiated by financial institutions.

Yip (2008) examined whether herding may cause heightened volatility in the foreign exchange market. The author investigated exchange rate systems and policies in Asia — specifically, China's exchange rate system reform initiated on 21 July 2005 and found that speculators herded due to excited expectations of revaluations, which drove the Chinese currency beyond its equilibrium level and thus creating a financial crisis.

Belke and Setzer (2004) investigated the influence of herding behaviour on currency crises. Similar to Banerjee (1992), the authors found significant herding due to informational cascades, which resulted in prices moving away from fundamentals and leading to increased volatility.

Kaltwasser (2008) examined herding behaviour in the foreign exchange market. Using a simple heterogeneous agent model of the exchange rate, the author estimated the dynamics of the socioeconomic configuration, optimistic and pessimistic excess demands and showed that investors are susceptible to changing their mind about the fundamental value of a particular asset purely as a result of contagion. This implies that investors tend to herd.

2.4.1.2.3 Investigating Herd Initiation

The literature on herding behaviour provides significant evidence showing that investment decisions among groups of investors can be highly correlated. However, very few papers investigate the problem of separating between the true decision leaders and those who simply mimic the actions of these leaders.

Bikhchandani et al. (1992) noted the importance of paying attention to early herding decisions. The authors proposed a fashion leader model, in which the

source of herding behaviour comes from the most experienced investor, acting first and attracting others to imitate him. However, the main drawback of this model is that the level of knowledge of the leader must be known with certainty. Boortz et al. (2013) found that information asymmetry is a key driver of herd behaviour, and private information is a significant advantage in financial markets. This means that those who hold more relevant data are “eligible” to become herd leaders.

Identifying and separating the herd initiators from the followers is a difficult yet very important task since it allows us to determine who has the ability to influence others to follow suit, and whether these herd initiators possess superior trading skills which can benefit their followers as a waterfall effect.

2.4.2 Disposition Effect

2.4.2.1 Understanding the Disposition Effect

“The disposition effect is defined as the tendency to sell winning investments early and hold on to losing investments” (Weber and Camerer, 1998). The authors estimated the difference in propensity to close a position, conditional on the investment being a gain versus a loss. The disposition effect, like herding behaviour, can potentially affect market prices, moving them away from their fundamental values (Grinblatt and Han, 2005; Frazzini, 2006; Shumway and Wu, 2006; Birru, 2015). The reason given is that selling assets that have increased in value to realise gains will gradually increase the price of the asset, whilst holding on to losing assets will push down the price of the asset further. Odean (1998) argued that the disposition effect results in traders withholding information from

the market, which consequently shifts asset prices away from their true values. Evidence supporting this argument is provided by Statman et al. (2006) who found that the disposition effect influences market-wide trading activity, subject to a bull or bear market. Moreover, Hartzmark (2014) found that traders' tendency to sell extremely profitable securities and to hold on to particularly loss-making securities within their portfolios, can lead to strong price effects.

The most popular theoretical framework, used in previous literature to explain the disposition effect, is the prospect theory proposed by Kahneman and Tversky (1979). The idea behind this theory is that when an individual has a choice between two or more outcomes, their behaviour will follow an "S"-shaped value function, where "the function is concave in the domain of gains and convex in the domain of losses" (Kahneman and Tversky, 1979), indicating that losses outweigh the gains.

Shefrin and Statman (1985) were among the first researchers to identify and define the disposition effect as the traders' tendency to close winning trades and hold on to losing trades. To measure the disposition effect, the authors (Shefrin and Statman, 1984) applied a behavioural model, which includes five factors:

1. **Prospect theory:** As mentioned earlier, the disposition effect may appear when investors face the choice between realising a small loss immediately, or waiting to see if the position will turn into a gain, or result in a more significant loss. Prospect theory implies that traders will choose the second option and hold on to a losing investment in the hope that the investment will turn into a gain in the future.

2. **Mental accounting:** This factor was discussed by Thaler (1980) and is related to the concept of tax swapping, such that investors use the difference between long-term and short-term tax rates when deciding when to realise gains versus losses. The reason is that realising a gain would result in a definite tax payment, while realising a loss would give the investor a tax credit or “rebate”.
3. **Regret aversion:** This factor arises when the traders’ regret for making a wrong decision prevents them from closing the losing position. Two emotions are in play in such a scenario that affect the investor’s behaviour: regret and pride. Kahneman and Tversky (1979) and Thaler (1980) argued that the first emotion overcomes the latter leading to individuals becoming passive and withhold decision-making when their investment losses value. Similarly, Shefrin and Statman (1985) illustrated that when investors realise that they sold a particular asset too early and the price continues to rise, they feel a sense of regret.
4. **Self-control:** This factor initially studied by Glick (1957) refers to the conflict between traders’ rational thinking and their emotional drives. Emotions can influence investors to hold on to losers and sell winners without any rational reasons behind this decision. Self-control may be dominant to the point that some traders will make up rules, such as accepting the loss only if the price declines by more than ten percent (stop-loss orders) (Kleinfeld, 2004).
5. **Transaction costs:** According to the strategy of Constantinides (1983, 1984) individuals should realise losses whenever transaction costs are absent.

The behavioural model of Shefrin and Statman (1985) examined the nature of investors' time differences in realising losses relative to gains. The authors used two datasets, the first is provided by Schlarbaum et al. (1978a) and is made up of panel information about individual stock trades by selected investors between 1964 and 1970. The second dataset was obtained from the Investment Company Institute. The Investment Company Institute publishes an annual Statistical Workbook that contains data on monthly purchases and redemptions of mutual fund shares from January 1961 to December 1981. The authors found significant evidence that tax concerns alone cannot explain gain and loss realisations, and that the disposition effect is widely evident in real world scenarios.

Odean (1998) proposed one of the most popular measures of the disposition effect, which accounts for both potential and actual gains and losses. By dividing the actual gain (loss) by the sum of both actual and potential gains (losses), one obtains the proportion of gains realised PGR (proportion of losses realised PLR) and can measure one's propensity to realise a gain or a loss given the opportunity to do so. The difference between the PGR and PLR is an estimate of an individual's disposition effect. Odean (1998) examined the trading records of around 10,000 investors from January 1987 to December 1993 and found that investors often prefer to sell winners rather than losers — this is not a rational trading strategy from a tax, transaction cost, or portfolio rebalancing perspective. This finding is similar to that reported earlier by Case and Shiller (1988). Odean (1998) explained his findings using 1) prospect theory and 2) that traders may hold losers because they believe these securities will generate more profits than the current winners.

Weber and Camerer (1998) suggested an alternative measure of the disposition effect, which is calculated as the ratio of the difference between the number of trades with realised gains and the number of trades with realised losses to the sum of these two parameters. They applied this method in an experiment where individuals buy and sell different shares, and where investors are allowed to sell or to hold both winners and losers. The results showed that when traders experienced losses, they were willing to hold these losing assets because the pain of a further loss is less than the pleasure of recovering the purchase price. Weber and Camerer (1998) explained their findings using a specific reference point — the difference between the purchase price (or the last period price) and the current price. When this difference reaches a certain value, the trader will sell the stock. According to Weber and Camerer (1998), traders prefer to sell more when the current price is above the purchasing price.

Shapira and Venezia (2001) analysed the disposition effect among a large number of professional (2,688) and independent (1,642) investors at a major Israeli brokerage house during 1994. The authors used the method developed by Schlarbaum et al. (1978a, b) and found that both professional as well as independent investors exhibit the disposition effect; however, this effect is more pronounced among independent investors. Moreover, the authors found that professionally managed accounts experience more frequent trading compared to independent accounts, which may explain the higher disposition effect among independent investors who prefer to hold losing investments rather than close their position. Their findings suggest that investors who follow a strict investment mandate are less likely to succumb to the disposition effect. Similarly, Locke and

Mann (2005) investigated whether “discipline” — adhering to a predetermined exit strategy measured by the speed of trading or by the avoidance of holding onto large losing positions — can be used to soften the disposition effect among retail investors. Using data from the Chicago Mercantile Exchange (CME) on 334 traders during 1995, the authors found that measures of relative discipline based on the first 6 months are associated with a trader’s success in the following 6 months. Moreover, traders who offset losses more quickly are more likely to be successful in the future; however, speed in realising gains is also a useful predictor of future success. The authors also found that traders who are more likely to hold on to large losses are less likely to be successful in the future. This evidence is consistent with the disposition effect. Similar evidence was also presented by Griffin et al. (2007) regarding institutional investors; however, the disposition effect is less pronounced relative to individual investors. Similarly, Aspara and Hoffmann (2015) investigated whether eradicating feelings of personal responsibility can decrease an individual’s tendency to exhibit the disposition effect. Specifically, the authors conducted three experiments that show the disposition effect can be reversed, when: 1) “prior investment gains are attributed to external factors while prior losses are associated with an individual’s own faults”, 2) “individuals invest other investors’ money”, and 3) when individuals have a “socially driven investment goal other than simply generating a financial gain”.

Other studies have investigated whether experience, as proxied by the number of trades executed, reduces the disposition effect. For instance, Shumway and Wu (2006) examined whether the disposition effect drives stock price momentum

using a dataset of 13,460 Chinese investors and firms from a large Shanghai-based brokerage firm. The authors found that a significant proportion of Chinese investors exhibit this behavioural bias. Investors with a higher disposition effect trade less frequently and in smaller volumes. Moreover, while past returns are not a good predictor of future returns for stocks traded on the Shanghai stock exchange, sorting stocks by net unrealised gain or loss of those investors with a high disposition effect results in a significant winner-loser spread of 7% per year. This suggests that the disposition effect has an impact on stock momentum. Moreover, Leal et al. (2010) examined the disposition effect of 1,496 individual investors in the Portuguese stock market and found noteworthy evidence of its influence, on the basis of trade frequency, volume, and value traded. The disposition effect was also present at the end of the fiscal year, despite of the fiscal effect, where investors realise losses in order to reduce their tax exposure. The authors also divided the data into bull and bear periods, and found that the disposition effect is more prominent in bull markets. The authors also defined sophisticated investors, as those who trade more frequently, with a larger number of transactions, and a larger total portfolio value. The authors also found an inverse correlation between investor sophistication and investor propensity to exhibit the disposition effect. Furthermore, Dhar and Zhu (2006) analysed the trading records of more than 50,000 individual traders at a major discount brokerage and found that wealthier individuals and those employed in a professional occupation exhibit a lower disposition effect. Moreover, trading frequency was also shown to reduce the disposition effect, suggesting that traders learn from their past trades to avoid this bias. Da Costa et al. (2013) examined whether trading experience erodes the disposition effect in a computer-

simulated stock market. The authors categorised individuals as experienced investors or inexperienced investors (undergraduate students). In addition, they simulated random computer-generated trade decisions as a control group. The authors found that both human groups exhibited the disposition effect, and that this bias is less prominent among experienced investors. These findings confirm earlier results by Shapira and Venezia (2001) that investor experience erodes the disposition effect. Since the automated trades did not exhibit the disposition effect, Da Costa et al. (2013) argued that this bias is caused by cognitive illusions.

Several studies have investigated how news impacts the disposition effect. For instance, Frazzini (2006) examined whether the disposition effect induces an underreaction to news, which may lead to return predictability. Using a dataset on 29,812 mutual fund holdings from January 1980 to December 2002 obtained from the CRSP/COMPUSTAT database, the author found that post-announcement price drift is most significant when capital gains and news are positively correlated. In addition, the magnitude of the change depends on the capital gain or loss experienced by the investor on the date of the event. Moreover, Li et al. (2014) used a multi-agent model to examine the disposition effect in the Chinese market. The authors found that negative news creates fluctuations in prices that are larger than those produced by good news. The authors' model categorised traders as either chartists, fundamentalists, or inactive traders. Results showed that chartists are more prone to the disposition effect; in addition, this type of trader is a key source of asymmetric volatility in the Chinese stock market. Focusing on information asymmetry, Dorn and Strobl (2009) used a dataset of transactions of 30,000 investors at a German brokerage

from 1995 to 2000 to investigate the impact of information asymmetry on the disposition effect. The authors found that the disposition effect among uninformed investors weakens after events that decrease information asymmetry. Moreover, the disposition effect among these uninformed investors becomes weaker in persistent winners and losers. Frydman and Rangel (2014) conducted a trading laboratory experiment to examine the possibility of reducing the disposition effect exhibited by individuals by making information about a stock's purchase price and capital gains (or losses) less salient. The authors compared two conditions: 1) a high-saliency condition where the purchase price of the stock is often displayed by the trading software, and 2) a low-saliency case where the price is not displayed at all. Their study shows that traders exhibit a disposition effect in the high-saliency scenario and that this effect is 25% smaller in the low-saliency case — indicating that it is possible to reduce the disposition effect by decreasing the saliency with which a stock's purchase price is displayed to the investor.

Brown et al. (2006) examined daily investor holdings from the Australian Stock Exchange from 1995 to 2000 and discovered significant evidence of the disposition effect. Nevertheless, traders executing larger investments are less affected by the disposition effect. This suggests that the disposition effect erodes altogether approximately 200 days after the purchase of the asset. Moreover, the house money effect tempers the disposition effect, and shareholder loyalty schemes also partially offset their relative preference for selling winning stocks.

Richards et al. (2011) examined 7,828 UK active individual traders with around 395,998 trades from July 2006 to December 2009. Using the empirical methods of Odean (1998) and Feng and Seasholes (2005), the author found that stop

losses, age and sophistication may reduce the influence of the disposition effect. Similarly, Bellofatto et al. (2014) analysed 51,098 retail investors from 1999 to 2012 and used the Markets in Financial Instruments Directive (MiFID) tests to determine the level of investor sophistication. They found that stop-loss orders, investment advice and financial sophistication reduce the disposition effect.

Singal and Xu (2011) examined how the disposition effect can create stock mispricing; they used a dataset of 2,363 actively managed US equity mutual funds from 1980 to 2007, obtained from the CRSP database. The authors used the measure proposed by Odean (1998), utilising 3-factor and 4-factor regression models, and found that around 30% of all funds exhibit the disposition effect and as well tend to underperform funds that do not exhibit the disposition effect by around 4% to 6% per annum. Additionally, disposition-prone funds attract much smaller fund flows, suggesting that investors are knowledgeable and tend to steer away from disposition-prone funds. As such, funds that exhibit the disposition effect have a higher rate of failure.

Ben-David and Hirshleifer (2012) investigated how investor beliefs and preferences influence trading patterns in relation to past returns. Using a dataset of 77,037 unique accounts from January 1990 to December 1996, the authors argued that the probability of selling as a function of profit is V-shaped, meaning that investors are more likely to sell extreme losers in short holding periods. Moreover, they found little evidence of an upward jump in selling at zero profit. Their findings show that there is no clear relation between realisation preference and trading patterns. Importantly, the authors concluded that the preference for selling winning stocks in preference to losing alternative stocks does not directly

affect the disposition effect; however, trading based on belief revisions is a more likely explanatory factor. An (2016) expanded on the work of Ben-David and Hirshleifer (2012) using data from the CRSP database, from January 1970 to December 2011, and argued that the disposition effect lowers current prices, affects equilibrium price dynamics, and cannot be fully explained by return predictors such as high volatility, momentum or reversals. Specifically, the authors found that the disposition effect is not a source of momentum, which is in contrast to the findings of Shumway and Wu (2006).

Rau (2015) investigates the disposition effect within two-person teams in comparison to individual traders. The author concludes that individuals investing jointly exhibit a larger disposition effect compared to individuals, since investor teams rarely realise losses and mostly choose to sell winners. This suggests that decision-dependent emotions may explain these differences in disposition between teams and individuals — such that, teams expressing high levels of regret, exhibit higher levels of disposition compared to individual investors.

More recently, several studies have investigated the relation between demographics and the disposition effect. Frino et al. (2015) studied the prevalence of the disposition effect among 46,289 individual traders in the Australian stock market, focusing on the effect of demographics and Chinese ethnicity on trading behaviour. The authors found evidence of the disposition effect across different categories of investors with the largest bias among investors of Chinese background, women, and older investors. Furthermore, other trading characteristics such as high trading frequency, round-size trading heuristics, and the level of portfolio diversification, were found to be accurate

forecasters of the disposition effect. Moreover, Tekçe et al. (2016) examined the disposition effect between 162,460 investors with around 64 million transactions during 2011 in the Turkish stock market. The authors found that age and portfolio values are positively related to the disposition effect, and females also tend to exhibit this bias more than males. Only 17% of investors did not show any significant evidence of the disposition effect.

2.4.2.2 Disposition Effect in the Forex Market

Very few studies investigate the disposition effect in the FX market. For example, O'Connell and Teo (2009) use a proprietary dataset consisting of a large group-set of institutional currency traders, in order to examine the effects of gains and losses on risk-taking behaviour. The authors found that institutional investors, unlike individual investors, are not as prone to the disposition bias. The reason is that institutions aggressively mitigate risk following a loss and slightly increase risk-taking behaviour after a gain. This asymmetry is more prominent at the end of the calendar year and especially among older and more experienced funds. Moreover, performance dependence is consistent with dynamic loss aversion (Barberis et al., 2001), as well as with overconfidence.

In a study on individual forex traders from October 2003 to May 2004, obtained from Oanda FXTrade, Nolte (2012) used a panel survival technique to examine the impact of limit orders, trading success, trade size, and experience on the disposition effect. The main findings show that the disposition effect is nonlinear, such that small profits and losses have an inverted disposition effect, while larger gains and losses exhibit the usual positive disposition effect. Moreover, the inverted part of the disposition effect is mainly driven by the cautious behaviour

of investors closing their positions with limit orders, including stop-loss and take-profit orders. The positive disposition effect is greatly intensified for investors who quickly and actively close their positions with market orders. In addition, the study finds that unsuccessful traders show a strong inverse disposition and that higher volume-trading traders are less prone to this bias.

Nolte and Voev (2011) created a model with a time-varying latent factor and examined investors' decisions to enter and exit a position in order to estimate the strength of various effects and the differences in trading behaviour across various types of traders. They found that the disposition effect decreases with investor size, in tandem with larger agents being more prone to the disposition effect at the portfolio level, but not with respect to profit or loss on single positions.

2.4.3 Sensation-Seeking

Zuckerman (1979, 1994) defines 'sensation-seeking' as a "trait for seeking varied, novel, complex, and intense sensations and experiences and a willingness to take physical, social, legal, and financial risks for the sake of such experiences". In financial markets, market sensation-seekers exhibit a pattern, such that they are not afraid of taking high levels of risk in order to achieve higher returns. Markowitz (1952b) argued that traders may choose to open many loss-making trades, in exchange for a small chance of a large gain. This type of behaviour can become addictive; hence sensation-seeking is often described as reckless trading behaviour.

Grinblatt and Keloharju (2009) stated that sensation-seeking could be detected when stock markets offer thrilling 'events' for individuals. Nevertheless, sensation

seekers are not pure risk takers, because unlike risk takers, sensation seekers agree to tolerate risk only in relation to its potential for novel and different experiences (Sunder et al., 2017). Nevertheless, Steenbarger (2007) argued that sensation-seeking leads to poor trading outcomes. In addition, Steenbarger argued this human bias is nearly impossible to control because such irrational behaviour in financial markets is inevitable (De Brabander et al., 1995; De Man, 2014).

According to Zuckerman et al. (1990) and Wong and Carducci (1991), there are two types of sensation seekers: 1) the low sensation seekers are people who show this bias in emotionally over-arousing situations in order to calm themselves, and they typically have low-risk tolerance, and 2) high sensation seekers, who look for thrilling situations regardless of the risk associated with the event. As such, sensation-seeking is negatively related to risk appraisal and positively associated with risky behaviour (Horvath and Zuckerman, 1993). Horvath and Zuckerman (1993) suggested that individuals who score high on sensation-seeking tests are more likely to engage in risk-taking behaviour in financial activities.

Rogers et al. (2013) studied risk-taking behaviour among investors by using measures including impulsivity, sensation-seeking, psychopathic personality traits and real life financial outcomes. Using a sample of 157 males and 179 females aged between 18 and 71, the authors concluded that sensation-seeking had a very large and significant influence on instrumental risk-taking among the 38 factors that were considered.

Studies such as De Brabander et al. (1995) and Statman (2014) separated sensation-seekers into two categories: knowledgeable sensation-seekers who are able to monitor and control their overconfidence, and less informed ones who are “blinded” by the cognitive error of overconfidence.

2.4.3.1 Drivers of Sensation-Seeking

2.4.3.1.1 Demographics

Sensation-seeking varies significantly among different demographics. Zuckerman (1971, 2005) stated that sensation-seeking declines in-line with a person’s age, and typically peaks at adolescence. Similarly, Reyna and Rivers (2008) argued that sensation-seeking and sensitivity to rewards grow from mid-childhood at roughly the age of 10 and peak in mid-adolescence between roughly the ages of 13 to 16. As such, sensation-seeking is expected to be higher among younger traders compared to older traders. Further studies, including Zuckerman et al. (1979), Ball et al. (1984) and Potenza et al. (2001), found that males tend to be greater sensation seekers than females, partly due to inherent physical traits.

Sjöberg and Engelberg (2009) examined the level of sensation-seeking among students using a questionnaire to measure emotional intelligence, attitude to economic risks and savings, general values, gender, age and experience in the finance industry. The authors found that students specialising in finance tend to have the highest level of risk tolerance.

2.4.3.1.2 Resource Availability and Status

Bradrania et al. (2016) and Sunder, et al. (2017) found that CEOs trade more aggressively, a behaviour driven mainly by the amount of resources available to them, coupled with their professional status and capacity to make executive decisions.

Specifically, Sunder et al. (2017) found that CEOs who engage in daring activities such as flying a private jet tend to spend resources on innovation more successfully. Using data on 103 pilots and 1,130 non-pilot directors from the Federal Aviation Administration (FAA), ExecuComp database and CEOs' biographies from 1993 to 2003, the authors found that pilot CEOs had more patents and citations, which is evidence of the positive correlation between the level of an individual's sensation-seeking and firm innovation outcome. Specifically, the number of patents that companies with pilot CEOs have is 70% more than companies with a non-pilot CEO, and the number of citations is 100% more. As for the board structure, the degree of sensation-seeking rises when the board is relatively small, when power is concentrated with the CEO through chairmanship of the board, and with a large number of insider directors.

Sunder et al. (2017) concluded that with a board structure where advising and supporting the CEO's sensation-seeking is greater than monitoring his behaviour, the effectiveness of the company's innovation activities is improved. Thus, risky innovative activities bring more exciting experiences with the result that CEOs will avoid conservative strategies in favour of riskier but potentially more profitable opportunities.

2.4.3.1.3 Entertainment

Mayall (2010) argued that traders do not always act rationally, and are often motivated by emotional sensations just as much as by financial imperatives. Hoffmann (2011) conducted a survey on Dutch investors and found their primary motivation for trading is its function as an enjoyable pastime activity, and not necessarily for the sake of increasing wealth. This echoes the work of Dhar and Goetzmann (2006) who found that investors buy stocks as a hobby and because it is something they enjoy doing. Similarly, Feingold et al. (1996) found that individuals engage in sensation-seeking activities to reduce negative feelings. For instance, Zuckerman et al. (1990) identified that susceptibility to boredom is a main driver of sensation-seeking. Willman et al. (2006) also concluded that excessive trading may emerge from boredom.

Dorn and Sengmuelle (2009) also examined entertainment attributes in trading activities using a sample of 1,000 investors at a German brokerage from January 1995 to May 2000. The authors found that entertainment factors are significant explanatory variables in a cross-sectional regression of portfolio turnover, where sensation seekers are believed to be younger, less educated, and less wealthy individuals.

Bauer et al. (2009) examined 26,266 option traders and 41,880 equity traders from January 2000 to March 2006, and showed that entertainment is key for sensation seekers in the options market in the Netherlands. Around 55.7% of options traders and 43.6% of equity traders stated that investing is just a hobby for them. The authors argued that gambling and sensation-seeking are important determinants of options trading.

2.4.3.2 Sensation-Seeking and Overconfidence

Grinblatt and Keloharju (2009) stated that the main difference between overconfidence and sensation-seeking is that sensation seekers are people who “live for the moment”, while overconfident individuals are those who have unrealistic and highly optimistic beliefs about their skills. Using information about Finnish investors’ driving records, tax filings and mandatory psychological profiles from January 1995 to November 2002, the authors found that sensation seekers trade more frequently and tend to perform poorly due to transaction costs. De Man (2014) proposed the use of double-crossover moving averages and contrarian Bollinger Bands as strategies for overconfident sensation seekers.

2.4.3.3 Risk-Taking in Gambling

In a recent study, Markiewicz and Weber (2013) conducted an experiment which included the trading records of 3,870 traders in addition to survey questions, and found that a domain-specific variant of risk-taking propensity — namely risk-taking in gambling as contrasted with risk-taking in investing — can predict the volume of an investors’ trades. The authors found that investors’ gambling risk-taking propensity, as measured by the Weber et al. (2002) Domain-Specific-Risk-Taking (DOSPERT) gambling subscale, increases the trading frequency of trades made, which consequently increases transaction costs; furthermore, this frequent trading behaviour is driven by sensation-seeking. Similarly, Hsieh (2013) examined individual and institutional investors in the Taiwan stock market and found that individual investor activity is driven by sensation-seeking, especially where given individuals perceive the stock market as a lottery game.

Grall-Bronnec et al. (2017) examined the similarities between trading and gambling using the data of 8 excessive traders, picked from a group of 221 outpatients seeking treatment for gambling addiction. The authors found several similarities between excessive trading and gambling in relation to diagnosis, trajectory and comorbidities. Like many sufferers of gambling, excessive traders also experienced several small early profits, chased their losses, and ended up losing control over their invested capital. Their findings support the notion of addictive-trading behaviour being a component of gambling disorders; however, they distinguished investing from gambling and excessive trading.

The literature presented shows that sensation-seeking leads to riskier trading strategies and the likelihood of incurring large losses. My research has revealed no studies that investigate sensation-seeking in the FX market. Hence, I measure this behavioural bias using a trader's margin utilisation, which serves as a proxy for risk preference. I discuss this indicator in more detail in the methodology section.

2.4.4 Inconsistent Behaviour

Inconsistent behaviour refers to the notion of an investor's decision-making in trading varying transitorily, outside the boundaries of their typical behaviour. This aspect is worthy of more detailed investigation, in order to better understand why traders deviate from their statistically mean-average behaviour.

2.4.4.1 Risk Appetite

Similar to sensation-seeking, inconsistent behaviour is partly driven by an investor's attraction to gambling. While this phenomenon might be expected

among individual traders, it has also been documented among institutional market participants such as Lehman Brothers, Long Term Capital Management, IndyMac and Bear Stearns (Jadlow and Mowen, 2010). According to Golec and Tamarkin (1998, p. 221) “the possibility of a large win is what lures them [inconsistent behaviour traders]”. The authors’ findings show that some tranches of institutional traders have a tendency to bet with a high degree of risk tolerance, therefore, inconsistent behaviour is closely related to investor risk preferences.

For instance, Barseghyan et al. (2011) showed that risk preferences are very unstable across highly related decision contexts between different types of insurance (home, auto, etc.). Moreover, risk preference can be influenced by information (Easley et al., 1996; Bikhchandani and Sharma, 2000; Peress, 2010; Easley et al., 2014), trading strategies (Boswijk et al., 2007; Goldbaum and Zwinkels, 2014), skills and knowledge (Park and Sabourian, 2011; Lin and Lin, 2014; Banerjee and Green, 2015), types of markets (Michaeli and Vila, 1996; Heath et al., 1999; Genesove and Mayer, 2001; Barberis and Xiong, 2009), among many other factors. Researchers have also examined risk appetite in financial markets.

Miccolis and Quinn (1996) defined risk appetite as the aggregate level, and the type of risk an entity is willing to bear within its risk capacity to achieve its strategic objectives and business plan. Sweeney et al. (2015) argued that risk appetite cycles are correlated with global growth cycles, which reach their peaks during times of crisis. Trader behaviour becomes largely driven by psychological fears and deviates from a trader’s regular/typical behaviour.

Illing and Aaron (2005) distinguished between actual and theoretical indexes of risk appetite. The former are based on statistical methods of different market estimation such as the Merrill Lynch Financial Stress Index (ML), the JPMorgan Liquidity, Credit, and Volatility Index (LCVI), the UBS Investor Sentiment Index (UBS), and the Westpac Risk Appetite Index (WP). By looking at all these indices together one can obtain an index quantifying overall risk appetite. Many researchers have also developed risk appetite indices. For instance, Kumar and Persaud (2002) developed a Global Risk-Appetite Index (GRAI) where they ranked assets by their riskiness and excess returns, and examined the relation between these two features. A positive relation indicates an increasing risk appetite and vice versa. Furthermore, Tarashev et al. (2003) developed the Risk-Appetite Index by estimating the statistical distribution of future asset returns using the historical patterns of asset prices, and by applying a Generalised Autoregressive Conditional Heteroscedastic (GARCH) model. Subsequently, using option prices with different exercise prices, the authors calculated the implied volatility, where the Risk-Appetite Index is the ratio of the left tails of the distributions of the asset return to the option price volatility. Gai and Vause (2004) expanded upon Risk-Appetite Index of Tarashev et al. (2003) by using the ratio of the full distributions instead of the ratio of the left tails. Wilmot et al. (2004) developed the Credit Suisse First Boston Risk-Appetite Index (CSFB), which is similar to the GRAI. The authors compared excess returns across assets with past price volatility by applying a cross-sectional linear regression and observing an upward-sloping correlation, thereby indicating a higher level of risk appetite.

Misina (2003) proposed that: 1) “changes in investors’ risk appetite will have monotonic effects on assets in different risk classes, where the impact on returns will depend on the riskiness of a particular asset”, and 2) “a change in the riskiness of an asset will not have monotonic effects on excess returns across different asset classes”. It follows that random changes in risk preference is a key attribute of inconsistent traders. In a follow up study, Misina (2005) investigated changes in risk appetite by creating an index that calculates changes in traders’ risk preferences based on popular trader opinion. The author identified three factors of risk appetite: 1) agent’s risk aversion, 2) demand for risky securities, and 3) the quantity of risky assets demanded. Consequently, one can explain observed changes in an investor’s portfolio based on changes in that investor’s risk appetite.

2.4.4.2 Noise Trading and Inconsistent Behaviour

Inconsistent behaviour is closely related to noise trading (De Long et al., 1990a); however, noise trading is a wider phenomenon that includes traders who deviate from fundamentals. As such, noise traders act differently when compared to rational investors, and their collective actions have the potential of moving asset prices from their fundamental values. Hence, noise trading can greatly increase the volatility of an asset even when there is no change in the fundamental risk of that firm. Figlewski (1979) noted that noise traders create hazards for rational ones, because they can destabilise financial markets long enough to create different anomalies (bubbles, crashes, ...). One reason why traders may choose to ignore fundamentals is because there may be an opportunity to earn excess returns due to short-term fluctuations in the price of an asset. Moreover, markets

take time to consume all fundamental information, thus investors may be able to identify market anomalies, such as the high dollar of the mid 1980s and the extraordinary price/earnings ratios on Japanese stocks in 1987-1989.

It may seem logical that young and inexperienced traders would exhibit inconsistent behaviour more often than experienced ones, since they are less informed about their abilities and more prone to succumb to behavioural biases. Nevertheless, Hayley and Marsh (2016) examined the performance of around 100,000 retail foreign exchange traders over two and a half years and found that retail traders act in a similar way to each other and their behaviour can be modelled and predicted.

2.4.4.3 Individual Trader Heuristic Decisions

Individual traders have neither the capacity, nor the time to analyse many assets in a short period of time; as such, they often rely on certain heuristics to simplify their decision-making process. Quoting Kahneman and Tversky (1974), “people replace the laws of chance by heuristics, which sometimes yield reasonable estimates and quite often do not” (p.32). According to Shah and Oppenheimer (2008), heuristics either (i) examine fewer cues, (ii) simplify their weighting, (iii) reduce the effort of reclaiming cue values, (iv) examine fewer alternatives, or (v) integrate fewer amounts of datasets. Similarly, Gigerenzer and Gaissmaier (2011) defined this phenomenon as “a strategy that ignores part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods”. The authors detected a trade-off between accuracy and time, or effort, when making a decision. This dilemma has been explained by Savage’s (1972) “small world” and “large world” assumptions.

Small world is a “perfect” world where all relevant alternatives, their consequences and probabilities are known. However, small world scenarios are rare in modern financial markets (Simon, 1979). Large worlds, on the other hand, are scenarios where (i) private information is present, (ii) costs (time, money, etc.) need to be paid for getting relevant data, and (iii) the future is uncertain. ‘Large world’ market conditions are more synonymous with actual market action, which it makes it very important to distinguish between large world and small world dynamics, since rational models do not work in imperfect financial markets. In large world situations, agents tend to base their decisions on heuristics, where less information and effort can yield more accurate results than applying a complex model.

Hertwig and Gigerenzer (2011) argued that inconsistencies in observed behaviour have often been perceived as conflicting with average stable behaviour. Nevertheless, the authors showed that the issue is not solely based on the inconsistent behaviour itself, but on the assumed existence of preferences. Using a theoretical framework, the authors explained behaviour as a function of heuristics’ interactions with the environment, rather than identifying different behavioural inconsistencies, and were able to accurately predict when behavioural inconsistencies are likely to occur.

Gigerenzer and Gaissmaier (2011) investigated heuristics as efficient cognitive processes that ignore some of the available information. Since using heuristics saves effort, the traditional argument has been that decisions based on heuristics have greater errors compared to “rational” decisions that are based on statistics and models. Nevertheless, for many decisions the assumptions of rational

models may not be met. As such, the authors tested formal models of heuristic inference and found that 1) individuals often base their decisions on simple heuristics in an adaptive way, and 2) ignoring part of the information can lead to more accurate decisions compared to weighing up and integrating all available information.

Several types of heuristics have been identified in the literature. I summarise some of the most popular below:

- **Representativeness heuristic:** This is explained as an individual's tendency to evaluate the probability of an uncertain event by the extent to which it is 1) similar in its fundamental characteristics to the parent population, and 2) reflects salient features of the process by which it is generated. For example, if a person assigns a high probability to the event that a data sample is generated by a random walk process, the underlying sample should be considered representative of such a process.
- **Recognition heuristic:** This occurs when an individual has to infer, which of two or more decisions will produce a better outcome. The recognition heuristic occurs when the individual recognises only one of these alternatives and not the other, and infers that it is the better decision.
- **Fluency heuristic:** This occurs when traders recognise all available alternatives, but choose the one they recognise to be the fastest. Making decisions based on this heuristic results in inconsistent behaviour since individuals are not making their decisions based on a rational evaluation of all options, but rather, simply choose the first option they recognise,

which may be very different from their average/typical decision type (Johnson and Raab, 2003).

- **One-clever-cue heuristics:** This heuristic occurs when an individual gives attention to one advantage of a certain decision and ignores all the other cues or disadvantages. This heuristic can differ among individuals since it is based on the way cues are perceived and assessed.
- **Trade-off heuristics:** This heuristic happens when individuals weigh information and cues in order to determine the optimal option among the alternatives. Within financial markets, DeMiguel et al. (2009) compared decisions made using this heuristic to 14 optimisation models, including Markowitz's mean-variance portfolio framework (among others), using 10 years of stock market data. The authors concluded that none of the complex optimisation models can reach the same positive result (returns, turnover, the Sharpe ratio) as the trade-off heuristic process.

In general, the literature implies that the more unpredictable the information environment, the more superior heuristic models become, relative to rational models.

Measuring inconsistent behaviour is a complex task. Given the studies presented above, I use a measure of risk appetite as a proxy for inconsistent behaviour, specifically, a trader's actual margin utilisation at the moment of placing the order. If this measure is not significantly different from zero, it is assumed the trader does not exhibit inconsistent behaviour. On the contrary, if the measure is statistically significant, then the trader is considered to exhibit inconsistent behaviour.

2.4.5 Information Advantage

Traditional financial theory postulates that all market participants have access to the same publicly disclosed information, which is already reflected in asset prices. Aldea and Marin (2007) defined such a situation as perfect symmetric information, where market participants receive the same information simultaneously. Moreover, investors are assumed to be rational and unemotional when allocating their capital to different investments. Nevertheless, many studies have shown that homogeneity among market participants does not hold in reality (Lyons, 1991, 1995; Frankel and Rose, 1995; Elliot and Ito, 1999; Frechette and Weaver, 2001; Evans, 2002), and investors exhibit many behavioural biases that drive them to deviate away from a common well-diversified market portfolio and trade irrationally for various reasons (Locke and Mann, 2005).

One reason why traders may choose to make decisions that are different from the predominant market consensus is because they may possess private information deemed to be valuable (Easley et al., 1996; Bikhchandani and Sharma, 2000; Easley et al., 2014). Thus, a heterogeneous expectations theory, which opposes traditional financial frameworks, embraces the notion that investors may possess different sets of information, and that these information differentials may result in superior returns in some cases and irrational behaviour in others. Consequently, private information in the hands of individual investors may lead to unique and risky trading decisions with the intention of realising abnormal profits.

2.4.5.1 Information Asymmetry

Hayek (1945) stated: “the utilisation of knowledge is not given to anyone in its totality”. Many studies have investigated information asymmetry in different situations. For instance, Coval and Moskowitz (1999) observed information asymmetry by analysing the influence of geographic proximity in the portfolio choices of US mutual funds. Krinsky and Lee (1996) and Cong et al. (2010) found a significant relation between information asymmetry and earnings announcements. Bikhchandani and Sharma (2000) found that herding behaviour may appear — because investors know that private information exists and seek to follow those who possess it. Therefore, herding arises due to informational cascades.

Boortz et al. (2013) created a model of herding behaviour based on information risk — “the probability of trading with a counterpart who holds private information about the asset” — and proposed that information asymmetry is a key determinant of herding behaviour. The authors analysed around 2.6 billion trades from the German Federal Financial Supervisory Authority (BaFin) and found that aggregate herding intensity increases with information risk. Similar results were also reported by Ramli et al. (2016) after investigating herding behaviour on the Indonesian stock exchange. The authors argued that information asymmetry leads to different stock price expectations, dividends and performance growth. Information asymmetry also appears to increase risk premiums and the volatility of stock prices and their returns, making uninformed traders highly prone to herd behaviour (Wang, 2000).

Chauhan et al. (2016) argued that information sharing may be distorted due to the needs of data owners, while Huddart and Ke (2007) found two factors that drive the information advantage: the uncertainty of company value and the precision of an agent's private information. They also showed that information asymmetry is positively correlated with the uncertainty of company value. Information asymmetry can arise from two sources or activities: 1) insider information, which may lead to illegal activities if traded upon, and 2) private information, generated by an individual's own research efforts or paying for privately collected data or research reports. I discuss these two sources of information asymmetry below.

2.4.5.1.1 Insider Information

One situation that leads to information asymmetry among market participants is insider information. The Financial Conduct Authority (FCA) defines insider information as information that is (i) not generally available, (ii) relates, directly or indirectly, to certain securities, and (iii) has the ability to have a significant effect on asset prices. As such, some investors may possess superior insider information through 1) "the membership of the administrative, management or supervisory bodies of an issuer of certain securities", 2) "holding of capital of an issuer of certain securities", or 3) "connections via their employment, profession or concurrent duties. Institutional investors typically have access to such insider information and are usually required to disclose their holdings of companies in which they have a vested interest or have a business relation". Retail investors are less likely to possess insider information, especially in the foreign exchange market where the majority of fundamental information is disclosed directly by

centralised federal agencies, such as central banks, at very infrequent time intervals. Hence, I do not expand on this topic further.

2.4.5.1.2 Private Information and Research

Obtaining private information and subsequently conducting private research requires individuals to expend their available time and resources. The advantage of conducting these activities to obtain private information is that the individual becomes more informed than the counterparty, leading to information asymmetry and a potential for excess returns. It follows that investors can be divided into two categories: informed and uninformed. The former are active investors who possess sufficient resources and apply additional effort to obtain valuable private information, while the latter do not — which typically leads to emotionally-driven trading decisions.

Abdioglu et al. (2015) defined the relationship between informed and uninformed investors as a situation where knowledge about a company's returns is unequally distributed among its investors. The authors also indicated that in today's financial markets, information asymmetry is considered to be inevitable, and that this phenomenon leads not only to changes in financial markets, but also to deviations in the behaviour of other market agents (Healy et al., 1999).

2.4.5.2 Studies on Private Information

Akerlof (1970) research was one of the first to investigate information asymmetry in financial markets. Using the car market as an example, the author illustrated that the seller is typically more informed about the asset being sold, and “knows which cars are good and which are bad” or “lemons”. Buyers on the other hand

are not as familiar with these new assets and do not have access to private information about the quality of the cars being sold. Consequently, due to this information asymmetry, good cars may be driven out of the market by the bad "lemons".

Similarly, Spence (1973) examined information asymmetry in recruitment, arguing that since the employer does not know the exact level of an individual's skills, the hiring process involves information asymmetry and may result in uninformed decisions on behalf of the hiring manager. In a related study, Figlewski (1979) investigated "subjective information" or "expert opinion" using data provided by professional analysts, brokers and banks. The author examined market efficiency with respect to this type of information, and found that subjective information brings uncertainty to decision-making processes since every source offers a different forecast. Costs associated with obtaining private information are the reason for information imperfection and should be taken into account as they have great influence (Stigler, 1967).

As a remedy to the issue of information asymmetry, Grossman and Stiglitz (1980) developed a model that is based on the assumption of informationally inefficient markets, including a risk-free asset with a stable return, and risky securities that offer stochastic returns. The authors stated that there are two types of traders: 1) informed traders who have access to information that allows them to identify and understand asset risks, and 2) uninformed traders who do not have the same privileges. There is a cost in terms of time and resources to be paid, should a trader choose to become more informed. The authors argued that prices reflect the information only partially, and that the aggregate level of market awareness

depends on the number of informed agents, which can vary widely. Hence, the whole financial market system can be described as follows: as informed agents generate gains based on superior private information, the greater the demand for private data among uninformed agents, and subsequently the less profitable this data tends to become as more individuals act upon it. Moreover, as the cost of obtaining private information increases, uninformed traders become willing to pay this cost. Furthermore, the expected effectiveness of uninformed individuals depends on the magnitude of noise trading. The authors concluded that there is a fundamental conflict between the efficiency with which markets spread information and the incentives of market participants to acquire information.

Stiglitz (2000) stated that the process of obtaining data can be costly, and showed how information asymmetry affects economies. The author described information as a commodity, where any piece of information is different from another, and its value cannot be fully estimated until the data provider shares it; however, when the information is shared the price is immediately adjusted to reflect that event. In general, the author concluded that economies (including financial markets) with imperfect information have very significant differences with the economies where information is symmetric and perfect.

Baik et al. (2010) investigated the role of information in relation to the geographical proximity of an institution's activities. Specifically, the authors studied the relationship between institutional investors' informational advantages and stock returns, where geographic proximity was used as a measure of data asymmetry between informed and uninformed agents. The authors stated intention was to examine and compare whether local or non-local investors traded

better. Local (in-state) investors are those who trade the securities of the country they live in, while non-local (out-of-state) investors are those who trade in foreign markets and assets. The study made use of multiple datasets such as the CDA/Spectrum Institutional (13f) Holdings from January 1995 to June 2007 including 171,989 firm-quarters, stock returns from the Centre for Research in Security Prices (CRSP), analyst forecasts from the Institutional Brokers' Estimate System (IBES), and financial data from Compustat (a financial database). Baik et al. (2010) used cross-sectional regressions of fractional local (non-local) institutional ownership on companies' characteristics, including: market-to-book, the log of market capitalisation, return volatility, turnover, S&P500 inclusion, stock price, cumulative market-adjusted return for the penultimate six months, cumulative market-adjusted return for the preceding six months, dividend yield and age. Their results showed that the highest quintile of local agents gain more profits, compared to the highest quintile of non-local agents.

As for information asymmetry, the in-state institutional investors are more informed than their out-of-state counterparts, and their trading activity is a strong predictor of future returns. Furthermore, data imperfection was found to be positively correlated with local ownership, such that organisations with a high level of data imperfection performed better, compared to those with low levels. Examples of such organisations include small or start-up companies, firms with high levels of volatility, and R&D (research and development) intensive companies. The findings of this study provide a good example of how costs may influence access to information, since obtaining information by local investors is significantly easier compared to non-local investors.

From a different perspective, Easley et al. (2014) studied private information content amongst hedge funds, using a model similar to Grossman and Stiglitz's (1980), where despite having all private information "investors do not have a clear idea of what strategies are used by other traders". Hedge funds also have access to private investment opportunities, such as direct investments in companies and options trading — financial products that mutual funds may be legally restricted from investing in. This gives hedge funds an advantage and the opportunity to provide effective risk-aversion investment strategies in equity markets. In the authors' model two assets are traded: a risk-free asset and a risky-equity asset. At the beginning of the trading session agents have one stock — they can choose to be "transparent traders" (mutual funds) or "opaque traders" (hedge funds), but to be the latter a cost must be paid, which represents the cost that hedge fund must pay to develop complex trading strategies. Opaque traders have a different information set and more investment opportunity diversity, such as foreign currencies, venture capital, commodities, options or precious metals.

Easley et al. (2014) also distinguished between different types of information that can lead to ambiguity: 1) exogenous data which includes forecasts about price dynamics, earnings reports, and other fundamental signals, and 2) endogenous information, which is related to uncertainty about the trading strategies of other investors. The authors simulated a decrease in the degree of ambiguity around hedge fund strategies and an increase in the cost of operating them — to find that the premium paid for equities increases, subsequently decreasing total welfare and the number of hedge funds in operation. They also estimated the demand, future wealth and expected effectiveness of these traders and found

that hedge funds appear to behave in a less risk-averse manner compared to mutual funds. As costs increase, and as ambiguity increases, a smaller number of traders tend to become opaque.

Evidence of information asymmetry in Chinese stock markets was found by Doukas and Wang (2013), where they examined whether differences exist in data availability between local A-share and foreign B-share markets. A-shares can be held and traded only by Chinese domestic traders, while B-shares can be purchased by foreign traders. In contrast to the study performed by Baik et al. (2010), the authors found that out-of-state investors possess more value-relevant, firm-specific information, compared to local investors, despite factors such as different accounting standards, language barriers and weak access to local information. The latter factors are also the reason behind higher premiums in the B-share market (Chakravarty et al., 1998; Chan et al., 2008). Furthermore, the authors found that Chinese investors are not as informative as they can be, and the reasons behind this are local market problems such as ineffective legal enforcement, limited trader protection and imperfect accounting-auditing systems. Such issues create a tendency to trade not on the actual information, but on rumours. As a result, Chinese stocks are more correlated with overall market movements, than with firm-specific information (Morck et al., 2000; Chan and Hameed, 2006). Foreign investors, on the other hand, cover their high costs of obtaining information by the profits generated through their skills and professionalism. Moreover, the stricter rules that apply to companies that want to list their shares in the B-shares market, such as the preparation of financial statements according to both Chinese Generally Accepted Accounting Principles

(GAAP) and the International Accounting Standards (IAS), ensure that investors obtain high-quality information about companies. As such, the B-share market has a higher level of investor protection and information transparency. Moreover, the authors established that B-shares discounts are the result of a downward price correction towards the fundamental value, once more firm-specific information is capitalised on by sophisticated foreign B-share investors. Furthermore, Doukas and Wang (2013) used vector autoregression (VAR) to examine the lead-lag relationship between the two investigated markets. Using data from October 1997 to September 2007, obtained from the China Stock Market and Accounting Research Database (CSMAR), the results showed that the B-share market leads the A-share market, and that the degree of information asymmetry decreases when regulatory reforms and market liberalisations occurred.

Another study by Sankaraguruswamy et al. (2013) investigated the frequency of news releases as an information asymmetry proxy. Specifically, the authors used the probability of information-based trading (Easley et al., 1996), the decomposed bid-ask spread (Huang and Stoll, 1997), and the permanent price impact of trades (Hasbrouck, 1991) as measures of information asymmetry, and found that information asymmetry tends to increase before and after events such as earnings or dividend announcements. Using data on 1,031 stocks traded on the New York Stock Exchange during 2004 and news announcement information from the website "www.MarketWatch.com", the study showed that there is a negative correlation between the frequency of public news releases and information asymmetry. The more frequent the stream of public information

announcements, the higher the trading intensity of uninformed investors. In addition, market regulators were identified as a key component affecting this frequency. As a conclusion, the study showed that uninformed investors do not react to information as fast as informed investors, which affects price dynamics in the wider markets.

Other researchers such as Ravi and Hong (2014) examined the nonlinear relationship between firm-to-investor and investor-to-investor information asymmetry using a sample of over 1,000 stocks traded on the New York Stock Exchange from January 1993 to December 2008. The authors found that when firm-to-investor information asymmetry increases, investor-to-investor information asymmetry tends to increase in parallel — but only up to a certain point after which it steadily decreases. Data imperfection reaches its peak between two extreme situations: the first extreme situation is when the company is completely transparent, such that inter-investor information asymmetry is zero, and the second situation is the exact opposite. The authors stated that since firms are opaque, it follows that inter-investor information asymmetry is also zero. The reason behind this is that in both situations investors either know everything or know nothing about the company. Hence, an increase in the level of transparency of a company does not always lead to an advantage for uninformed traders since inter-investor information asymmetry may still increase, resulting in liquidity reduction and an increasing cost-burden on capital growth.

Abdioglu et al. (2015) studied how information asymmetry affects foreign institutional investors' desire to invest in US equities. They aimed to explain why out-of-state traders take a big interest in US assets, despite the Sarbanes-Oxley

Act in 2002, which introduced significant compliance costs and had the potential to reduce US firms' performance. One of the reasons is firm-level disclosure and information transparency that reduces information imperfection. Using information on three indices, 18 different foreign countries, and 2,752 unique firms from the Thomson Reuters 13F database over the period 1999-2012, the authors studied how increasing firm-level disclosure influences the decision-making process of passive investors such as banks and insurance companies, and active investors including public pension funds, investment companies and independent investment advisors. Passive investors do not usually spend money on acquiring private information because of prohibitively high costs, as such they rarely put pressure on the managers of their investee companies to disclose more information. Passive investors on the other hand are more willing to obtain private data. The authors found that, in general, foreign institutional investors prefer large companies with high turnover, low ownership concentration, relatively safe institutional environments (i.e. strong accounting standards and legal frameworks), and the avoidance of markets with government expropriation risk. The Sarbanes-Oxley Act came into force in order to improve the institutional environment by increasing the amount of disclosure, which resulted in a decline in costs related to obtaining information. As for active traders, the Sarbanes-Oxley Act decreased their competitive edge since the disclosure of company information has been made a legal requirement under this act.

Another study was conducted by Tourani-Rad et al. (2016), who investigated foreign IPOs of Chinese companies listed on the Hong Kong stock exchange to find if the choice of listing location influences the information environment for

foreign IPO companies, compared to those who list their stocks for the first time solely in their home market. Using intraday tick data from 1996 to 2012, the authors examined the asymmetric information component of the bid-ask spread and concluded that foreign IPO firms have the same degree of data imperfection as Hong Kong IPO firms. However, on Chinese exchange markets IPOs have higher levels of priced information asymmetry compared to foreign IPOs.

Chauhan et al. (2016) examined the impact of information advantage on stock prices in the Indian stock market and found that the information content of insider trading follows an inverted U-shaped function in relation to controlling ownership. The reason for information asymmetry is due to poor investor protection, resulting in a higher level of uncertainty regarding a firm's value. The study distinguished between two sources of inside information: 1) founders and families hold most of the corporate ownership structure in emerging markets, which allows them to use private information to obtain an advantage against minorities and other traders, thus increasing the degree of information asymmetry between insiders and outsiders, and 2) performance of regulations, where stricter regulations lower insiders' willingness to use private information to make abnormal profits. Due to less stringent enforcement of regulations, data imperfection estimates are high in India. To measure information asymmetry within institutional ownership the authors used price responses to earnings announcements, product market competition, the percentage of independent directors and price 'informativeness' (awareness) as model parameters. Moreover, they employed the database maintained by the Center for Monitoring Indian Economy (CMIE) from January 2007 to October 2012. The results showed that: price informativeness reduces

insider information content, traders who possess negative private information start selling immediately, and that insider trading becomes less frequent, but more informed.

Akbas et al. (2016) investigated the relationship between information asymmetry and the level of board member influence upon the company. In every company, corporate managers are required to keep information private and confidential; however, interacting with many people may lead to information leakage to sophisticated traders, who may then gain a competitive edge in trading. Corporate directors are insiders who have privileged information about their organisations, while sophisticated traders do not have direct access to such information, but can get it through exchanges with corporate directors. The more frequent these communications and exchanges, the higher the probability of inadvertent information leakage. The same applies to the number of people who possess private data (Steele, 1989). The authors argued that companies with a higher degree of director connectivity are easier to analyse for upcoming earnings surprises. The data used in the study was composed from different sources including information about connections of corporate directors and executives from the BoardEx for the period January 2002 to December 2011, proxies from Ivy OptionMetrics, data about institutional ownership and insider trading data from Thomson Financial, and analyst forecasts included in the I/B/E/S database. Using the monthly level of short interest, weekly order imbalances of institutional traders, and the ratio of monthly option volume to stock volume as measures for informed trading, the authors developed a novel identification strategy which studies the information flows between corporate directors and sophisticated

traders. The study found highly significant relationships between all measures of informed trading and future stock returns for firms with more connected boards.

2.4.5.3 Relation Between Noise Trading and Private Information

De Long et al. (1990a) investigated noise trading and argued that noise has a great impact on financial markets since rational investors have a limited willingness to take positions against noise traders. According to Black (1986), noise trading occurs because of irrational trading behaviour amongst uninformed investors. This is in opposition to what classical theorists such as Friedman (1953) and Fama (1965) propose, where rational thinking agents always defeat noise traders thus returning the price to its fundamental value. The reasons why noise prevails in the market is because aversion to fundamental risk can hold arbitrageurs back even when they have infinite time horizons (Shiller et al., 1984; Campbell and Kyle, 1993), and according to Figlewski (1979) a long-time period is needed for noise traders to run out of money. Noise trading is unpredictable and creates risk even when there is no excess fundamental risk in the financial market.

With respect to information asymmetry, there are two main issues. First, noise traders do not have the ability to obtain private information, especially in the foreign exchange market. Second, noise traders believe they have special information about the future price of the risky security a result of “pseudo signals” produced from technical analysis, economic consultants or stockbrokers. Generally, noise trading often drives certain anomalies in financial markets such as volatility clustering, mean reversion in asset prices, bubbles and crises.

In general, the literature on information advantage illustrates the inevitability of information asymmetry. In this research, I concentrate on retail traders in the foreign exchange market. As such, I argue that the Forex market has limited potential for insider information to be effective in generating excessive returns, with every participant being able to get all relevant publicly-disclosed data. However, some individual traders may still be able to obtain private information on order flow, which this information can be used to gauge the direction of the market. Hence, I include this proxy in my analysis.

2.5 Research Questions

In general, this thesis investigates the performance and behaviour of retail FX traders, which is an area that has not been intensely explored by academics due to limited access to high quality, detailed data. Hence, I employ a detailed transaction level dataset on retail FX traders, which allows me to control for trade-specific characteristics and provide refined insight — compared to the existing literature — about heterogeneity in performance and expectations among retail FX traders in the EUR/USD market to shed light on the characteristics and dynamics of foreign exchange markets. I also examine what proportion of traders possess skills, which further highlights that there may be significant variation in performance and expectations among traders at any given moment. Such an analysis emphasises the importance of understanding that the FX market is not homogenous and that heterogeneity should be acknowledged as a constant and natural phenomenon. Additionally, I study how external factors, such as heightened market volatility, and endogenous behavioural biases affect trader skills. This allows us to understand the micro dynamics of the FX market and provide insight into how market factors as well as trader behaviour affect an individual's trading skills. Furthermore, this is the first study to my knowledge to examine the effect of multiple behavioural biases, simultaneously, on trader skills.

Very few researchers have investigated heterogeneity among retail FX traders, and those who did (Abbey and Doukas, 2015; Haley and Marsh, 2016) had data limitations which prevented them from controlling for trade characteristics when testing for heterogeneity in performance, and from investigating heterogeneity in expectations. Hence, the research questions I aim to investigate are: 1) how do

trade-specific characteristics affect heterogeneity in performance among retail FX traders, and 2) do retail FX traders exhibit heterogeneity in expectations, such that their forecasts vary significantly from the market average? I make use of transaction level data on retail FX traders, which allows me to delve deeper into micro dynamics of this market and shed light on how individual traders make decisions, that on average, diverge significantly away from the market consensus. Such an analysis illustrates that heterogeneity in financial markets is a natural and persistent phenomenon, which should not be overlooked or simply labelled as noise.

The analysis on heterogeneity among retail FX traders raises another research question. Given that traders have different views about the market at any point in time, and thus trade differently, this implies that some traders perform well while others perform poorly. Some papers have investigated this topic in the context of retail FX, such as Abbey and Doukas (2015) who apply a factor model to assess whether traders exhibit outperformance. Their analysis essentially examines only one of the three skills which I investigate in my thesis, which is the ability to add value in absolute terms to an investment. My research contributes to the literature on trading skills by answering the following: 1) do individual traders have the ability to correctly predict future price movements, and 2) do they have the ability to adjust their position in a profitable manner based on their expectation of the change in market prices? To do so, I adopt an alternative approach to capture the different skills of a trader using three metrics: 1) success rate, 2) return on investment, and 3) big hit ability. This analysis allows us to estimate what proportion of traders in the retail FX market truly possess genuine trading skills.

While a trader's skills may be endogenously determined by one's innate characteristics, external market factors, such as volatility, may play a critical role in shaping the outcome of these skills. The literature shows that there is a negative relation between volatility and performance, where higher volatility negatively impacts the performance of investors. As such, I investigate how heightened market volatility affects the three trading skills mentioned above. Specifically, does heightened market volatility have a negative impact on a trader's skills? The high level of uncertainty in the market should cloud the judgement even of the most skilled traders, such that the high volatility will have a detrimental impact on a trader's ability to correctly predict price movements and as well as generate a positive return.

The evidence presented in the literature and in this thesis shows that market dynamics can be greatly affected by the skills of the individual traders. Moreover, a trader's skills are determined by one's personal biases, which affect the person's decision-making process. This leads me to investigate the following research question, which is a topic that has not been researched previously: how do behavioural biases affect the skills of retail FX traders? Specifically, I examine five behavioural proxies which are: 1) herd initiations, 2) disposition effect, 3) sensation seeking, 4) inconsistent behaviour, and 5) information advantage. In general, a skilled trader is expected to, 1) initiate the herd and is deemed as a leader by others, 2) exhibit the disposition effect by realising small yet consistent profits, 3) be a sensation seeker and use leverage to exploit even the slight price movement, 4) exhibit inconsistent behaviour to adjust to the dynamic market conditions, and 5) have an information advantage, which may be in the form of

private analyses of the market. This analysis highlights the importance of understanding behavioural biases and how they impact a trader's performance.

Section 3. Hypotheses, Data and Analytics

3.1 Hypotheses Section

There has been limited research that investigates the characteristics and skills of individual retail FX traders, and examines how external as well as endogenous factors impact trader skills.

Based on literature review and the research gaps presented above I propose the following hypotheses in order to shed light on 1) the degree of heterogeneity found in retail FX markets, 2) the variation in the skills exhibited by the different traders, 3) how market uncertainty impacts a trader's skills, and 4) how an individual's endogenous biases affect their abilities.

3.1.1 Hypothesis 1: Measuring heterogeneity among traders

The research question I aim to investigate is whether there is heterogeneity in performance and expectations among retail traders in the EUR/USD foreign exchange market? I develop the following hypotheses:

Hypothesis 1.A:

- H0: There is no significant heterogeneity in performance among retail traders in the EUR/USD foreign exchange market.
- H1: There is significant heterogeneity in performance among retail traders in the EUR/USD foreign exchange market.

Given the methodological and data limitations of previous studies discussed in the literature (Abbey and Doukas, 2015; Hayley and Marsh, 2016), I use a

detailed transaction level dataset, which allows me to apply a more refined methodology to control for trading characteristics that may impact variations in performance among traders, including trade duration, limit orders, trade direction, volume, and trading frequency. I expect to find evidence of and persistence in heterogeneity among retail FX trader, which implies that heterogeneity is not a momentary lack of consensus among market participants, but is rather a constant characteristic that defines the microstructure of the market.

Hypothesis 1.B:

- H0: There is no significant heterogeneity in expectations among retail traders in the EUR/USD foreign exchange market.
- H1: There is significant heterogeneity in expectations among retail traders in the EUR/USD foreign exchange market.

I draw on the literature on heterogeneity in expectations (Ito 1990) at the institutional level and argue that retail traders in the FX market also exhibit heterogeneity in expectations such that their forecasts of the EUR/USD spot rate are significantly different compared to the average market consensus.

3.1.2 Hypothesis 2: Identifying genuine trading skills

The second research question I aim to investigate is whether some retail FX traders possess genuine trading skills, such that they are able to consistently predict future price movements (i.e. more than half of a trader's positions generated a profit), add value in absolute terms (i.e. the sum of all profits and losses is positive) and adjust the size of their position based on their confidence

in their forecast (i.e. increase their position when they expect the change in future prices to be large, and vice versa)?

Hypothesis 2.A:

- H0: There is no significant evidence that retail FX traders consistently predict future price movements (Success Rate \leq 50%).
- H1: There is significant evidence that retail FX traders consistently predict future price movements (Success Rate $>$ 50%).

Given the evidence in the literature that retail FX traders have the ability to correctly predict future price changes in the short-term (which may be due to the use of momentum strategies) I expect that a large number of traders in my sample will exhibit a Success Rate greater than 50%. Given that some traders will exhibit the ability to successfully predict future price movements, this further contributes to the literature on heterogeneity by showing that there is significant variation in traders' ability to predict movements in market prices.

Hypothesis 2.B:

- H0: There is no significant evidence that retail FX traders add value in absolute terms (ROI \leq 0%).
- H1: There is significant evidence that retail FX traders add value in absolute terms (ROI $>$ 0%).

While retail FX traders may have the ability to correctly predict future price changes in the short-term more than half of the time, fewer traders possess the ability to add value in absolute terms to their initial investment. This may be due

to the elevated levels of volatility in the FX market, coupled with the traders' use of high leverage levels which can result in large losses if the market turns against them. As such I expect that the majority of traders will have a negative ROI which indicates that these traders lose money over time. As such, the variation in the use of leverage and the timing of trades among traders is expected to result in a heterogeneous distribution of returns. This would support the argument that there is significant heterogeneity in the ability of traders to add value to an investment.

Hypothesis 2.C:

- H0: There is no significant evidence that retail FX traders adjust the size of their position based on their confidence in their forecast ($BHA \leq 0\%$).
- H1: There is significant evidence that retail FX traders adjust the size of their position based on their confidence in their forecast ($BHA > 0\%$).

I expect that few retail FX traders will adjust their positions based on their confidence in their forecasts as it is highly unlikely that these traders will possess superior fundamental information on foreign exchange rates which will drive them to adjust the size of their positions accordingly. Given that some traders are expected to change their exposure over time depending on their confidence in their decisions, this implies that heterogeneity is a dynamic and persistent characteristic of the market.

3.1.3 Hypothesis 3: The impact of volatility on trading skills

The third research question I aim to investigate is how heightened market volatility affects the skills of individual FX traders?

Hypothesis 3.A:

- H0: There is no significant evidence that volatility impacts the ability of retail FX traders to correctly predict future price movements.
- H1: There is significant evidence that volatility impacts the ability of retail FX traders to correctly predict future price movements.

I expect that high market uncertainty will have a negative impact on a trader's ability to predict future price movements, as market information becomes less accurate, more volatility and traders rely more on sentiment rather than economic analysis.

Hypothesis 3.B:

- H0: There is no significant evidence that volatility impacts the ability of traders to add value in an investment in absolute terms.
- H1: There is significant evidence that volatility impacts the ability of traders to add value in an investment in absolute terms.

I expect that elevated market uncertainty will have a negative impact on a trader's skills. This is because the high level of uncertainty will cloud the judgement of traders. In addition, when traders base their simulations on historical low volatility data, and are then faced with a high volatility market situation, this renders their analysis inaccurate. Hence, when volatility is high, price fluctuations can be very significant such as that they result in significant losses to traders, which can be hard to recover. Given the above argument, I expect that elevated levels of market volatility will be detrimental to an individual's skills.

3.1.4 Hypothesis 4: The impact of behavioural biases on trading skills

The fourth research question I aim to investigate is how trader behaviour impacts the skills of retail FX traders; specifically, how behavioural biases affect 1) the performance, 2) the ability to add value in absolute terms and 3) the ability to adjust the size of the position.

I examine five behavioural indicators to capture behavioural features such as herd initiations, disposition effect, sensation seeking, inconsistent behaviour and information advantage.

Hypothesis 4:

- H0: There is no significant evidence that behavioural biases affect the skills of retail FX trading population.
- H1: There is significant evidence that behavioural biases affect the skills of retail FX trading population.

I expect that skilled traders 1) are herd initiators, 2) exhibit the disposition effect whereby they are more likely to realise profits compared to losses, 3) are sensation seekers, 4) exhibit inconsistent behaviour and 5) do not have an information advantage since they are trading in the foreign exchange market where it is unlikely that they possess superior fundamental information about foreign exchange rates.

3.2 Data and Methodology

3.2.1 Retail Trading Operations

Foreign exchange trading traditionally refers to over-the-counter (OTC) SPOT (the single payment option trading) currency contracts in the interbank market. SPOT automatically converts the option to cash when the option is successful, giving a pay-out. The SPOT option contract is not cancellable by selling. The standard settlement time frame is usually two business days (T+2), with some exceptions settling on different dates such as USD/CAD (T+1).

Although this OTC product is popular in the interbank market, it became increasingly popular following its simplification in the retail domain. FX trading in the retail domain is performed through trading a rolling spot FX product, a product that is more appealing to the retail community rather than the SPOT currency contracts in the interbank market. The contract has the same underlying asset of the two-day forward, but with no physical cash settlement date. The settlement cash amount at the end of each day acts as a rollover (simultaneous operation of buying one value date in exchange for selling another value date) resetting the delivery to the next trading day. The difference in prices between the two value dates results in creating a fee (usually a small amount) and this amount is defined as a rollover fee (or a swap fee).

Essentially, retail FX traders engage in trading by speculating on currency fluctuations without the need to worry about any physical delivery of their position. In reality, a CFD (contract for difference) is marked to market in real time and is settled at the end of each trading day. Thus, any potential gains or losses are

realised at the end of each trading day, and the trader's position is rolled over to the next trading day if it has not been closed by the trader.

National Futures Association (NFA), the self-regulatory organisation for the U.S. futures industry was one of the first that attempted to standardise rolling spot FX trading and its market makers. Retail foreign exchange dealers (RFEDs) are defined as "individuals or organisations which act, or offer to act, as a counterparty to an off-exchange foreign currency transaction with a person who is not an eligible contract participant". The transaction is either:

- A futures contract, an option on a futures contract or option contractor.
- Offered or entered into, on a leveraged or margined basis, or financed by the offerer, counterparty or person acting in concert with the offerer or counterparty on a similar basis" (National Futures Association 2010).

Following the NFA official description of the RFED operations, the Financial Services Authority (FSA) (Financial Services Authority 2011), now the FCA (Financial Conduct Authority) also commented on its functions and described them as "not to be limited to the intermediation function but also serving as an agent and/or deal as a principal" making the RFED essentially a broker-dealer. Broker-dealers play a vital role in the financial markets by providing access to any category of market participants such as investors, speculators, hedgers and arbitrageurs.

Specifically, RFEDs act as market makers by offering both bid and ask prices to their customers (the traders). This is done by injecting vital liquidity and serving as a counterparty to any of their trades. The traders are eligible to place trades,

and the market maker holds an obligation to fill the order at either the market or the requested price.

Traditionally, after a dealer receives an order it can reduce his inventory in two ways:

- by matching the customer order with another customer from his order book. The dealer has no control of the entry of trades since customers always instigate customer trades. This, though, does not limit the dealer's control since it has the ability to attract customers by offering advantageous rates (price shading); or
- by passing the customer order to the interdealer network (acting as a broker only) from dealer to dealer, with the deal exiting the interdealer network only when it is offset by one or more customer orders.

The above is not the usual case for the RFED. Due to the nature of their product offering (high leverage financial instruments) they prefer to take a certain inventory themselves, but also stand ready to buy or sell in the interbank market if they are required to minimise their inventory risk. They do this by standing as the sole counterparty to its customers by providing liquidity and facilitating the creation of orderly markets.

On the other hand, banks do not enjoy holding inventory for more than a trading day. However, individual banks do not represent the market as a whole — since if every dealer in the market place targeted zero inventory then the sum of all signed order flow would be zero, which is usually not the case.

Regarding trading operations on the Anonymous broker, a trader begins by opening an account with the broker. To do so, the trader needs to provide personal identification information, which is verified by Anonymous and kept private. After the account is approved, the trader is able to deposit funds into their account in order to trade. Typically, the trader would transfer funds from his personal banking account to that of the broker, who in turn credits the trader's brokerage account with an identical amount in the base currency chosen by the trader. Once the funds are available in the trader's account, they are able to open positions using contracts for difference (CFDs) where they can have either long or short positions to a certain currency pair. All products available to the trader are displayed on the trading platform with all relevant real-time information, including the bid and ask quotes, the swap rate, minimum lot size, among other characteristics of the contract. The trader is then able to go long or short the currency pair either by a simple click of a button which is available on the chart of that currency pair, or by executing an algorithm, which will execute trades automatically when certain criteria are met. Similarly, the trader is able to close an open position either manually by a click of a button, or by specifying certain criteria in the algorithm, which would in turn automatically close out the position. Some of these criteria include, take-profit which would be executed once a certain amount of unrealised profit has been accumulated, and a stop-loss which is a predetermined level that limits a trader's loss should the price move adversely to the position direction. A trader is able to withdraw the funds in his account at any time (subject to paying all unrealised losses and due fees) to his bank account. Given this empirical setting, several parameters are recorded by the broker, which are used in my analysis.

3.2.2 Data. Descriptive Statistics

The dataset I use is obtained from a foreign exchange broker, which I call Anonymous, and contains 4,119,479 transactions in the EUR/USD currency pair executed by 21,300 retail FX traders from February 2011 to October 2013. The database is filtered to exclude any dummy accounts and as a result all trading is based on real money. The platform is active only from Sunday through Friday 21:00 GMT on Sunday till 21:00 GMT on Friday. Mark-to-market reconciliations of open trading positions take place at 21:00 GMT each day. For each trade, the platform records the value of the trade in U.S. dollars, the position direction, the time-stamp, and the type of the order, whether it is a market or limit order. Around 68.32% of positions are personally closed by the traders while 13.36% and 18.32% of positions are closed due to stop-loss and take-profit orders, respectively. In addition, I calculate several trader characteristics, which are presented in Table 1.1. The average trader balance is USD 1,806 with the largest account balance equalling USD 361,306. This shows that the Anonymous trading platform attracts small retail as well as larger traders. On average, around 46% of a trader's positions on Anonymous are long, which shows that traders engage in both long and short positions in order to exploit price movements in both directions. With respect to the average trade duration, I find that the mean across all traders is around 1 day. This indicates that traders on Anonymous are day traders who tend to close their positions at the end of each trading day in order to avoid exposure to overnight market volatility. I find that the average volume traded is around USD 20,933, with the largest position size equalling USD 7,611,111. Moreover, I find that the mean trade frequency over the life of a trader is 193 trades. Finally, the average account life of a trader is 243 days. This

suggests that many individuals cease their trading activities on this platform after 243 days either voluntarily by withdrawing their capital from their account, or involuntarily as a result of losing all their capital due to trading.

The independent variables that are used in my analyses include the following:

- Career Success: the average success rate of a trader over a specified period of time;
- Career ROI: the average return on investment of a trader over a specified period of time;
- Duration: the average duration of a trade for each trader;
- SL: the proportion of trades of a trader that are triggered by a stop loss order;
- TP: the proportion of trades of a trader that are triggered by a take profit order;
- Long: the percentage of trades of a trader that are long positions;
- Volume: the average position size of a trader measured in USD; and
- TradeFrequency: the number of trades executed by a trader.

Table 1.2 presents the correlation matrix of all the above-mentioned variables. We notice that the correlation between Career SR and Career ROI is not very high at around 12%. This underscores my earlier argument that each of these performance measures captures a different skill of the trader, and are thus generally independent of one another. Career SR has a relatively higher correlation with the other independent variables compared to Career ROI. Hence, all my models that make use of ROI have generally low explanatory power as will

be shown in the results section. Looking at some of the other large correlations, I find that the SL and Career SR variables are negatively correlated (-0.34), which is intuitive since the higher the proportion of stop loss orders executed, the more losing trades a trader incurs, and the lower their success rate. Similarly, the TP and Career SR variables are positively correlated (0.31) meaning that the higher the proportion of take profit trades executed, the higher the number of profitable trades a trader realises, and the higher the success rate.

3.2.3 Methodology

3.2.3.1 Performance Measures

I begin by introducing three performance measures, which are used throughout this thesis.

3.2.3.1.1 Success Ratio (SR)

The Success Ratio (SR) or “win ratio” is the percentage of winning trades relative to all executed trades, and is used to measure the trader’s ability to consistently predict future price changes. Many papers have adopted the *SR* as a simple method to investigate investors’ ability to forecast short-term and longer-term excess returns (Hartzmark, 1991; Nicolosi et al., 2009; Villanueva, 2007; Alquist and Kilian, 2010). The *SR* can be mathematically expressed as:

$$SR_i = \frac{\sum_{j=1}^n Z_j}{n}, \quad (1.1)$$

where SR_i is the proportion of trades of trader i that were profitable, Z_j takes the value of one if trade j was successful and zero otherwise, and n is the total number of trades executed by the trader.

Hayley and March (2016) suggested their variation of this measure. Instead of trades they take a number of successful days and divide it by the number of total trading days. Nevertheless, this variation was used due to the authors' lack of access to transaction level data. The obvious drawback of this measure is that it does not consider the actual size of the win. For instance, a trader can lose many times or days, but the profitable ones can cover all these small losses. In order to provide a better picture of the performance of FX traders, I also use two alternative performance measures: the return on investment (ROI) and the big hit ability (BHA).

3.2.3.1.2 Return on Investment (ROI)

ROI is a very popular instrument for estimating both individuals' and funds' performance. Menezes et al. (2015) mentioned the importance of this ratio and defined it as the profit of an investment divided by the cost of the investment. The *ROI* ratio shows the per-period profitability of the individuals, and how their capital was invested during the observed time. I can write the *ROI* for each trader i during time period t as:

$$ROI_{i,t} = \frac{\text{Net Profit}_{i,t}}{\text{Balance}_{i,t}}, \quad (1.2)$$

where $Net\ Profit_{i,t}$ represents the realised and unrealised profit of trader i on day t , and $Balance_{i,t}$ represents the balance of the trader up to day t , and includes *Net Deposits* and *Net Profits* prior to day t .

The reason why I include both realised and unrealised profits is because unrealised profits can be very significant and ignoring this component would give an unrealistic view of a trader's performance during a given trading period.

A positive *ROI* indicates that the trader has the ability to add value to an initial amount of investment, whereas a negative *ROI* means that the trader is actually decreasing his initial wealth.

3.2.3.1.3 Big Hit Ability (BHA)

This measure allows us to estimate a traders' skill in adjusting the size of their position contingent on their confidence in their expectations about market prices future movements. BHA was originally proposed by Michael L. Hartzmark (1991). Hartzmark (1991) defines *BHA* as taking "his [trader's] largest position (make his larges bets) when the highest returns are expected". Leuthold et al. (1994, p. 460) wrote that *BHA* is "being on the "right" side of the market when large price changes occur".

Hartzmark (1991) firstly assumed that the magnitude of the price change has a strong relation with to the probability of the right prediction. Thus, even a small amount of correct expectations can be very profitable, if a trader guessed the direction of a large price movement. Basically, this method of trading assumes a lot of small losses and few very big wins, that keep investor's level of profitability high. As for the method of estimating *BHA*, the author suggests a simple

regression proposed by Henriksson and Merton (1981) and Cumby and Modest (1987) to test the forecasting ability and investment performance of investors. The magnitude of the price change $R(t)$ linearly depends on the net position held by the trader $LS(t)$. The formula can be expressed as follows:

$$R(t) = a' + B'LS(t) + e(t) . \quad (1.3)$$

where $e(t)$ is a normally distributed error term. $LS(t) > 0$, if the agent is net long, and vice versa. A $B' \geq 0$ implies “superior” predicting ability (i.e. positive BHA), while a $B' < 0$ implies that the trader is an “inferior forecaster”.

BHA is a very important measure since it clearly indicates whether the trader can “read” the market and thus decide the right time for buying or selling the asset. This ability is crucial for retail traders who cannot afford to lose a lot of money, or who usually do not have access to private information, etc.

3.2.3.2 Testing for Heterogeneity among Retail FX Traders

3.2.3.2.1 Heterogeneity in Performance

In order to test for heterogeneity in performance among foreign exchange traders, I start by using the method proposed by Hayley and Marsh (2016), which is based on empirical evidence showing that some traders exhibit significant trading skill, thus outperforming a four-factor currency model (Abbey and Doukas, 2015).

I test for cross-sectional heterogeneity in performance by regressing the j^{th} trade success rate, which takes the value of 1 if the trade was successful and 0 otherwise, on the career success rate (i.e. the average success rate) over all previous trades. If performance is constant over the trading career of a trader, or

if differences in success are only temporary, then the coefficient of the career success rate will be statistically insignificant. It follows that there exists significant heterogeneity in performance if the coefficient is statistically significant and positive. I control for trading characteristics such as trade duration, limit orders, position direction, volume, as well as trading frequency. The model can be expressed as:

$$SR_{i,j,t} = Career\ SR_{i,j,t} + Duration_{i,j,t} + SL_{i,j,t} + TP_{i,j,t} + Long_{i,j,t} + Volume_{i,j,t} + TradeFrequency_{i,j,t} + e(t), \quad (2)$$

where $Career\ SR_{i,j,t}$ is the average career success rate over all trades of trader i , excluding the j^{th} trade. Hence, the control variables are the averages for each trader up to, but not including trade j , and include $Duration$, the average duration of a trade for each trader, SL and TP , the proportion of trades that are triggered by stop losses and take profit orders, respectively, $Long$, the proportion of long positions, $Volume$, the average volume traded, and $TradeFrequency$, the number of trades executed by a trader. I run a series of logistic regressions on the full sample of traders as well as on subsamples chosen according to the number of trades executed. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for the career stage of the trader. These subsamples are as follows: first ($N \leq 10$), early ($10 < N \leq 25$), middle ($25 < N \leq 50$), and late ($N > 50$) trades. Moreover, I repeat all the above-mentioned models; however, using the ROI performance measure instead of the success rate. Specifically, the model can be re-written as:

$$ROI_{i,j,t} = Career\ ROI_{i,j,t} + Duration_{i,j,t} + SL_{i,j,t} + TP_{i,j,t} + Long_{i,j,t} \\ + Volume_{i,j,t} + TradeFrequency_{i,j,t} + e(t),$$

where $ROI_{i,j,t}$ is the trade-level return on investment for each trader, and $Career\ ROI_{i,j,t}$ is the average career return on investment over all previous trades of trader i , excluding the j^{th} trade. Note that I report the intercept for Model (2a), which does not include trader fixed effects; however, there is no intercept for the other model variations that include trader fixed effects. The reason is that including an intercept would result in perfect correlation with the trader fixed effects, meaning that the model cannot be estimated.

In order to compare my results to those presented by Hayley and Marsh (2016), who only have access to data that is aggregated on a daily basis, I repeat the above analyses on daily aggregated data of the success rate. For instance, if a trader executes a total of three trades in a given day, where two of these trades result in a gain and the other in a loss, then the trader's success rate on that day is 2/3. I fit a linear model on the calculated success rate percentages; moreover, I dichotomise the daily success rate percentage, such that the daily dummy success rate equals 1 if the percentage success rate is greater than 50% and 0 otherwise. This allows me to run a model comparable to that done by Hayley and Marsh (2016). Model (2) can be rewritten for daily aggregated data as:

$$SR_{i,t} = Career\ SR_{i,t} + Duration_{i,t} + SL_{i,t} + TP_{i,t} + Long_{i,t} + Volume_{i,t} \\ + TradeFrequency_{i,t} + e(t),$$

where $SR_{i,t}$ is the trader's daily success rate (which is the percentage success rate for the linear model and a binary success rate for the logistic model as

mentioned earlier), and $Career\ SR_{i,t}$ is the average career success rate over all previous trading days of trader i , excluding the t^{th} day. Similarly, all other control variables are computed up to, and excluding the trades on day t .

I repeat the daily-aggregated model using the ROI measure, such that:

$$ROI_{i,t} = Career\ ROI_{i,t} + Duration_{i,t} + SL_{i,t} + TP_{i,t} + Long_{i,t} + Volume_{i,t} \\ + TradeFrequency_{i,t} + e(t) ,$$

Where $ROI_{i,t}$ is the return on investment for each trader on day t , and $Career\ ROI_{i,t}$ is the average career return on investment for each trader up to, but not including day t .

3.2.3.2.2 Heterogeneity in Expectations

The access to transaction level data allows me to apply the simple yet robust method proposed by Ito (1990) to test for heterogeneity of trader expectations. This technique requires the estimation of individual trader effects, which the author argues arise from constant individual bias and not due to the use of different models. To explain this method, consider that there are j traders in the sample, and that each trader's forecast at time t can be decomposed into a common structural part based on publicly available information, $f(I_t)$, and an individual trader effect, denoted by g_j . It follows that a trader's forecast at a given time frame t can be formally expressed as:

$$S_{j,t}^e = f(I_t) + g_j + u_{j,t} , \quad (2.1)$$

where, $S_{j,t}^e$ is the forecast or expectation of trader j at time t of the spot exchange rate, and $u_{j,t}$ is a random error term. Similarly, the cross-sectional average expectation at time t across all traders can be written as:

$$S_{AVG,t}^e = f(I_t) + g_{AVG} + u_{AVG,t} , \quad (2.2)$$

where $S_{AVG,t}^e$ is the average expectation across all traders at time t , g_{AVG} is the average individual effect, and $u_{AVG,t}$ is the mean of the error terms. If I assume that the common information $f(I_t)$ is accessible by all traders and comprises of a constant term, then normalising such that $g_{AVG} = 0$, and subtracting equation (2.2) from (2.1) would result in:

$$S_{j,t}^e - S_{AVG,t}^e = g_j + (u_{j,t} - u_{AVG,t}) , \quad (2.3)$$

The coefficient estimates of the individual trader effects, g_j can be obtained by regressing the difference between a trader's expectation and the average expectation of the spot exchange rate at time t , given by $S_{j,t}^e - S_{AVG,t}^e$ on a constant term over the sample period. A statistically significant g_j means that a trader's expectation or forecast is biased compared to the average expectation.

Note that in equation (2.3), it was not necessary to define the underlying structure of the common information set, $f(I_t)$ as long as this information is assumed to be publicly disclosed and available to all traders. The composite error term in equation (2.3) has a mean of zero and no autocorrelation if $u_{j,t}$ is cross-sectionally and serially uncorrelated, and the information set, $f(I_t)$ is the same to all traders.

Ito (1990) argues that if the individual trader expectations of future spot exchange rates extends to idiosyncratic coefficient terms on the information set $f(I_t)$, then equation (2.3) needs to be modified as follows:

$$S_{j,t}^e - S_{AVG,t}^e = g_j + (\beta_j - \beta_{AVG})(f(I_t)) + (u_{j,t} - u_{AVG,t}) . \quad (2.4)$$

Equation (2.4) allows us to test for individual trader effects, g_j as well as idiosyncratic effects, $(\beta_j - \beta_{AVG})$. In this study, I include a two-period lag of the information coefficient in order to examine the impact of idiosyncratic effects on heterogeneity of expectations.

3.2.3.3 Testing the Impact of Market Volatility on Trader Skill

In this section, I investigate the impact of market volatility as an external factor on trader skill.

To do so, I estimate a series of models similar to Model (2) where I regress the j^{th} trade success binary variable or *ROI* on the market volatility in the EUR/USD currency pair in the current period as well as in the previous 10 trading days³. If traders can profitably exploit and extract information from market uncertainty, then the volatility variables would exhibit a positive coefficient. On the other hand, if volatility proves to be detrimental to a trader's skills, then the volatility coefficients will be negative. As such, the general models I estimate are:

³ I do not estimate the impact of volatility on *BHA* since the latter cannot be computed on a daily or weekly basis due to lack of variation in the volume traded by traders.

$$\begin{aligned}
SR_{i,j,t} = & Career\ SR_{i,j,t} + Duration_{i,j,t} + SL_{i,j,t} + TP_{i,j,t} + Long_{i,j,t} \\
& + Volume_{i,j,t} + TradeFrequency_{i,j,t} + Volatility_{t-q} \\
& + e(t),
\end{aligned} \tag{3.1}$$

and

$$\begin{aligned}
ROI_{i,j,t} = & Career\ ROI_{i,j,t} + Duration_{i,j,t} + SL_{i,j,t} + TP_{i,j,t} + Long_{i,j,t} \\
& + Volume_{i,j,t} + TradeFrequency_{i,j,t} + Volatility_{t-q} \\
& + e(t),
\end{aligned} \tag{3.2}$$

where $Career\ SR_{i,j,t}$ and $Career\ ROI_{i,j,t}$ are the career success rate and return on investment over all previous trading days of trader i up to but not including trade j , respectively. The control variables are the averages for each trader up to, but not including trade j , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. As for market volatility, I use different proxies as follows:

- Model (3.1.a) and Model (3.2.a): $Volatility_{t-q}$ is the daily standard deviation of spot price changes on day $t-q$ where $q = [0, 1, \dots, 10]$;
- Model (3.1.b) and Model (3.2.b): $Volatility_{t-q}$ is a dummy variable that is equal to 1 for each day $t-q$, where $q = [0, 1, \dots, 10]$, if the standard deviation of spot prices on day $t-q$ is greater than the 70th percentile of standard deviations over the previous 30 trading days;
- Model (3.1.c) and Model (3.2.c): $Volatility_{t-q}$ is a dummy variable that is equal to 1 for each day $t-q$, where $q = [0, 1, \dots, 10]$, if the standard deviation

of spot prices on day $t-q$ is greater than the 80th percentile of standard deviations over the previous 30 trading days;

- Model (3.1.d) and Model (3.2.d): $Volatility_{t-q}$ is a dummy variable that is equal to 1 for each day $t-q$, where $q = [0, 1, \dots, 10]$, if the standard deviation of spot prices on day $t-q$ is greater than the 90th percentile of standard deviations over the previous 30 trading days.

All models include time and trader fixed effects.

As a robustness check for Model (3.1) and its variations, I aggregate the success rate of traders on a daily basis to examine the t^{th} trading day aggregate success rate on market volatility. The general model I estimate is written as:

$$\begin{aligned}
 SR_{i,t} = & Career\ SR_{i,t} + Duration_{i,t} + SL_{i,t} + TP_{i,t} + Long_{i,t} \\
 & + Volume_{i,t} + TradeFrequency_{i,t} + Volatility_{t-q} \\
 & + e(t) .
 \end{aligned} \tag{3.3}$$

3.2.3.4 Quantifying Behavioural Biases

In this analysis, I examine the impact of behavioural biases on trader skill. I use three performance measures, which are the Success Ratio (SR), Return on Investment (ROI), and Big Hit Ability (BHA) as defined earlier, and five behavioural indicators: herd initiations (HERD), disposition effect (DISP), sensation seeking (MU), inconsistent behaviour (INCON), and information advantage (INFO). For each of the performance measures, I run a linear model, given by Model (4.1), which uses the continuous value of the performance measure, and a logistic model, Model (4.2), which uses the dichotomised version of the performance measures. The dichotomised SR variable takes the value of

1 if SR is greater than 50% and 0 otherwise. The dichotomised ROI variable takes the value of 1 if $ROI > 0\%$ and 0 otherwise. Finally, the dichotomised BHA takes the value of 1 if $BHA > 0$ and 0 otherwise.

3.2.3.4.1 Herd Initiations

Herding behaviour is popular in financial markets (Cont and Bouchaud 2000, p. 174). It is common that individual investors join/follow the herd when they are concerned how others evaluate and make sound decisions i.e. stock market bubbles. The dynamics of herding behaviour can be explained as follows: individuals start forming a crowd, individuals then observe other individual actions and derive information from them, ignoring their own information and following the actions of others.

This condition does not test the traditional herding effect (previously performed with price dispersions) per se but the individuals who are capable of initiating a herd. In trading, this translates to an investor who has the ability to influence the investment decisions of others. Ideally, a herd leader typically exhibits the following characteristics: 1) has access to a significant number of market participants through trading platforms, 2) can initiate herding (stampede) behaviour by prompting others to follow suit, and 3) can consistently lead the herd such that this individual is recognised as the group leader.

This study investigates here who is able to initiate a herd and specifically, which traders are capable of not pulling, but initiating a herd. These will presumably be leaders who will initiate a group of people and be followed or observed by traders probably from their network. These traders who are capable of initiating a herd

are also deemed risky, as in ‘more dangerous’ for the dealer and always influential.

In order to measure the tendency of an individual to become a leader (herd initiator) I calculate the correlation coefficients r^i between the *Net Open Positions* of each trader i at time t denoted by NOP_t^i and the dealer’s $NOP_{t-\Delta}^D$ at time $t - \Delta$, where Δ is a time lag [$\Delta = 5, 10, 15, 30$ and 60 minutes]. I only calculate correlations between each trader’s positions and the dealer’s *NOP* at these five time lags due to the significant computational power required for these calculations. Moreover, I chose these time lags because they are the typical data frequencies that are available to traders on the MT4 platform.

To test the significance of the correlation I calculate the t-statistic as $t - \text{stat} =$

$$\frac{r^i}{\sqrt{\frac{1-(r^i)^2}{N-2}}}$$

with a critical value of $N-2$ degree of freedom. A correlation between a

trader *NOP* and the dealer *NOP* will imply that a herding effect exists.

A strong positive correlation would indicate that the trader is leading the herd, since the dealer’s lagged *NOP* (which represents the predominant opinion of traders on the platform) is moving in the same direction as the trader’s position. On the other hand, a negative correlation implies anti-herding behaviour since the trader is trading in the opposite direction of the majority.

I test the significance of the correlations between each trader’s positions and the dealer’s *NOP* at the above-mentioned time lags and find that the 15-minute time lag correlation is the most significant correlation. Hence, I focus my analysis on this time lag.

3.2.3.4.2 Disposition Effect

The second behavioural bias I examine is the disposition effect which is defined as the tendency of a trader to realise profits prematurely while holding on to losses for too long. In other words, this means that traders close winning positions as a sure gain while keep losses open in hope that they will turn into a gain.

I use Odean's measure to estimate an individual's disposition effect (Odean 1998), which considers the actual, and potential trades of trader i during 1 day trading timeframe. The proportion of gains realised (PGR_i) and proportion of losses realised (PLR_i) are defined as:

$$PGR_i = \frac{N_{gr}^i}{N_{gr}^i + N_{gp}^i} \quad PLR_i = \frac{N_{lr}^i}{N_{lr}^i + N_{lp}^i} ,$$

where N_{gr}^i (N_{lr}^i) is the number of trades by trader i with a realised gain (loss), and N_{gp}^i (N_{lp}^i) is the number of potential trades for trader i with a gain (loss).

The disposition effect (DE) of a trader (Odean 1998, p. 1781) i is then calculated as

$$DE_i = PGR_i - PLR_i \quad (2) ,$$

where $-1 \leq DE_i \leq 1$. A positive DE_i indicates that a smaller proportion of losing traders are closed compared to the proportion of winning positions closed, in which case trader i exhibits the disposition effect.

The significance of the disposition effect in equation (2) is tested by the following t-statistic:

$$t = \frac{PGR_i - PLR_i}{SE_i},$$

where the standard error SE_i is:

$$SE_i = \sqrt{\frac{PGR_i(1 - PGR_i)}{N_{gr}^i + N_{gp}^i} + \frac{PLR_i(1 - PLR_i)}{N_{lr}^i + N_{lp}^i}},$$

A disadvantage of the equation (2) is that PGR_i and PLR_i measures may be sensitive to trading frequency (Odean 1998). As such, I used two alternative measures of the disposition effect as robustness checks which are not sensitive to volume size and trading frequency.

The first measure was proposed by Weber and Camerer (1998) and considers the difference between the number of trades with realised gains by trader i and the number of trades with realised losses relative to the number of all trades, this can be expressed as:

$$DE_i = \frac{N_{gr}^i - N_{lr}^i}{N_{gr}^i + N_{lr}^i},$$

where $-1 \leq DE_i \leq 1$

If the number of trades with realised gains matches the number of trades with realised losses, then there is no disposition effect.

The second measure was proposed by Dhar and Zhu (2006) and is expressed as:

$$DE_i = \frac{N_{gr}^i}{N_{lr}^i} - \frac{N_{gp}^i}{N_{lp}^i}.$$

I find that all three indicators are highly correlated and do not change the results of my analysis as such I focus my analysis on the results using Odean's measure.

3.2.3.4.3 Sensation Seeking

The third behavioural bias I examine is sensation seeking which is a trader's tendency to look for experiences that are novel, complex and challenging by way of taking social and financial risks to achieve these experiences. In financial trading sensation seeking occurs when a trader uses varied strategies and high leverage ratios in order to achieve significant positive returns, where by the trader feels an addiction and a thrill when participating in the market.

It follows that sensation seekers are described as people who are more willing to use leverage (in this case margin), thus exhibiting reckless behaviour. In many instances people start by demonstrating reckless behaviour which then transforms into sensation seeking.

From a psychophysiological perspective, the central nervous system is affected by the individual differences in the cortical arousal thresholds, the levels of enzymes and neurotransmitters (Hogan, 1997). Evidence can also be traced in the genetic origins of dopamine receptor levels linked to the venturesome personality (Cloninger et al. 1996; Farde et al. 1997).

Margin utilisation is a dimensionless variable that shows the relation between the margin required to maintain the position and the available collateral at a given point in time. Margin utilisation serves as an efficient benchmark for the identification of trader risk preference within the broker-dealer book. Margin utilisation is defined as follows:

$$MU_t^{(i)} = \frac{P^{(i)}}{L} / (B^{(i)} + PL_t^{(i)}).$$

where $MU_t^{(i)}$ represents margin utilisation of the i^{th} trader at time t ; $P^{(i)}$ represents the trading position notional value calculated in standardised units; $B^{(i)}$ is the collateral of the i^{th} trader and $PL_t^{(i)}$ is the floating profit or loss of the i^{th} trader at time t .

As stated before, the margin utilisation serves as a proxy for sensation seeking.

I also use the squared margin utilisation (MU^2) in order to capture any potential non-linear relation between margin utilisation and skills, since high margin utilisation can lead to not only high returns but significant losses as well.

3.2.3.4.4 Inconsistent Behaviour

The fourth behavioural bias I examine is inconsistent behaviour which is an attribute of an individual who chooses to act in such a way that cannot be justified or explained by their normal (average) behaviour. In other words, inconsistent traders are individuals who switch or change their activity momentarily or all the time, resulting in actions different from their average behaviour.

To capture the inconsistent behaviour, I draw on the field of gambling sciences. Since bettors crave a skewness in outcomes over mean returns (Golec and Tamarkin, 1998, Cowley 2013) by escalating bets it provides them with the opportunity for big wins. Golec and Tamarkin (1998, p. 221) described the cogent state as the attractiveness of the possibility of a large win. To win big, bettors should be allowed to bet big. This bet differential (the difference between

maximum and minimum bets) is the benchmark that casinos use to limit their risk exposures in this discrete game.

In my study, I argue that traders exhibit consistent behaviour when their risk appetite does not vary significantly around their mean risk tolerance. Conversely, inconsistent behaviour arises when the trader adopts a varying risk exposure. As such in order to measure inconsistent behaviour one should examine the margin utilisation over time whereby this risk proxy is expected to vary significantly with each trade, thus signifying inconsistent behaviour.

To measure inconsistent behaviour, I use the standard deviation of margin utilisation σ_i^{MU} for the i^{th} trader, where a value that is close to zero implies that trading behaviour is consistent. On the other hand, a significant non-zero value means that the trader exhibits inconsistent behaviour.

3.2.3.4.5 Information Advantage

The final behavioural bias that I used in this research is information advantage which represent an individual that “does not play by the rules”. In game theory (Milchtaich 2014, p. 1) all trading terms and conditions can be considered as rules in a trading game. If there is an incentive to bend the rules in this game, then the rules will be bend. In this sense, rules act not just as a constraint, rather as a resource of gain and in certain situations where instructions are not clear they are subject to interpretation.

Taking into account that there exists a trade-off between the advantage of having more information and the cost of obtaining it a trader will optimise this function in order to achieve superior returns. This information is used to a trader’s advantage

by identifying and measuring overpriced opportunities by keeping a risk-averse behaviour.

In the foreign exchange market, insider information is assumed to have minor impact since it is unlikely that retail traders will possess private superior fundamental information. Hence, prices (exchange rates) should reflect all available information (news, public releases, etc.), where every market participant has access to the same set of information at all times.

From an interdealer broker⁴ perspective, interdealer brokers operate within tight margins, and they profit mostly from the spread as a source of constant gain. Taking any inventory risk means that an interdealer broker should be able to offset the order in the interdealer market covering at least his costs (the spread). Therefore, traders who exhibit short-term momentum when they trade cause interdealer brokers to immediately offset the order in the interdealer market without giving them any opportunity to hold inventory.

This short-term momentum i.e. the time between placing the order with the broker and how fast the market reacts to the trade and capturing the spread cost, is the proxy that captures information advantage.

This phenomenon has also been investigated at the institutional level, whereby short-term momentum in extreme levels becomes momentum ignition, which is a strategy that triggers a number of positions and creates price movements (Tse et al. 2012, p. 6).

⁴ An interdealer broker (IDB) is a financial intermediary that matches transactions between broker-dealers and other financial institutions.

To measure the information advantage of a trader I calculate the average time Δ it takes to cover the spread cost after placing an order. For each position opened there is a time t and an opening price $p(t)$, where the time Δ^n is calculated for each trade as:

$$\begin{cases} p(t^1 + \Delta^1) - p(t^1) = \text{average spread} \times \text{trade direction}^1 \\ \dots \\ p(t^n + \Delta^n) - p(t^n) = \text{average spread} \times \text{trade direction}^n \end{cases}$$

The set of equations above defines the time to profit Δ^n for each i^{th} trade. The

final characteristics of the trader will be the average value $\Delta = \frac{\sum_{i=1}^n \Delta^i}{n}$.

3.3 Results and Discussions

3.3.1 Testing for Heterogeneity

3.3.1.1 Heterogeneity in Trader Performance

3.3.1.1.1 Transaction Level Analysis

I begin by running Model 2 and its variations on the transaction data, and present the results in Table 2.1.1.1. The results of Model (2a) on the full sample of traders show that the career success rate of an individual is positively related to the j^{th} trade success rate. This is indicated by the statistically significant coefficient of 3.3892. This implies that traders exhibit an autoregressive pattern in their performance, which can be interpreted as evidence of temporal heterogeneity, since each trader's performance is changing throughout their career.

The average trade duration of a trader is positively related to the j^{th} trade success rate as indicated by the significant coefficient of $2.5e-7$. While this number may seem small, recall that *Duration* is measured in seconds. Hence, the longer the mean duration of trades, the higher the likelihood of having a positive success rate on a future trade. The reason is that trades are initially opened in a net loss to the trader due to the bid-ask spread, hence, it may take some time before the price moves in favour of the trader in order to cover the bid-ask spread and generate a profit.

With respect to limit orders, I find that the *SL* parameter has a negative coefficient of -0.3964, which suggests that traders are placing stop loss levels that are very close to the market price. Hence, any slight change in the price would trigger the

stop loss order. Consequently, these traders may be placing suboptimal stop loss levels as part of their trading strategy, which increases the likelihood of a zero-success rate on a future trade due to a stop loss being triggered prematurely. Similarly, for the take profit variable, *TP*, I find a negative coefficient of -0.02 meaning that (compared to a market order) the take profit limit set by the trader is suboptimal.

I find a coefficient of -0.3628 for the *Long* variable, which indicates that traders who predominantly rely on long positions tend to have less successful trades as they are less likely to take advantage of downward movements in prices. Moreover, this may suggest that these traders have strict trading strategies that limit excessive short positions, which are deemed to be riskier in general.

Regarding *Volume*, I find a significant coefficient of -0.0309 meaning that traders with larger positions historically tend to be unsuccessful in future trades, which may be a sign of overconfidence. Hence, as traders are more confident in their decisions and invest larger amounts, they may underestimate risk, resulting in losses on future trades.

Finally, the transaction level details allow me to investigate “experience” in trading using *TradeFrequency* i.e. number of trades executed by a trader. In this way, trading experience is not a reflection of the real age of a person but the actual experience a trader has. I report a significant but very small coefficient of $1.0e-5$ for the *TradeFrequency* variable, which suggests that gaining experience by executing more trades does not improve a trader’s success rate. This result is similar to the finding of Haley and Marsh (2016) who show that traders do not learn to trade better over time. Considering an alternative interpretation of

TradeFrequency as a proxy for overconfidence, the coefficient implies that overconfidence only marginally improves a trader's success rate.

Model (2a) does not include year and month and trader fixed effects, and has an R^2 of 7.75%. In order to account for time and trader fixed effects, I repeat the same analysis on the full sample; however, I include year and month fixed effects. The results of Model (2b) are largely the same as those of Model (2a). Most importantly, the *Career SR* coefficient is 3.3848, which is very similar to what I obtained in Model (2a). This further supports the evidence of significant heterogeneity in performance among retail FX traders. I obtain similar results for all the other control variables, thus I avoid repeating the discussion. The R^2 of Model (2b) is equal to 7.78%.

Next, I divide the data into the different phases of a trader's careers: first ($N \leq 10$), early ($10 < N \leq 25$), middle ($25 < N \leq 50$), and late ($N > 50$) trades. I repeat the analysis in order to examine the impact of career success on future trading as a trader matures and progresses through his trading career. The results are reported in Table 2.1.1.1 under Models (2c), (2d), (2e), and (2f), respectively, for each subsample.

I find that the coefficient for *Career SR* is statistically significant and positive across all models, and it increases as a trader gains more experience through trading. Specifically, the coefficients for Models (2c), (2d), (2e), and (2f) are 1.0889, 2.7852, 3.4236, and 4.6991, respectively, which indicates that the estimated coefficient increases as a trader progresses through his trading career, since the average career success rate is estimated more accurately as the number of transaction observations increases. This means that heterogeneity in

performance among traders persists and increases as traders progress in their trading career. My results are similar to the evidence presented by Hayley and Marsh (2016), who showed that there exists significant persistence in heterogeneity in performance among retail FX traders.

Regarding *Duration*, I find a positive coefficient across all models, since it may take prices sometimes to move favourably before covering the spread and turning a profit.

With respect to limit orders, I report a negative coefficient for the *SL* variable across all models, which is similar to the result on the full sample. As for the *TP* variable, I find that it is initially positive in the early career of the trader and then decreases until it becomes negative as the trader matures, as shown by the coefficients of 0.2614, 0.1979, 0.12332, and -0.0596 for models (2c), (2d), (2e), and (2f), respectively. This means that at the start of their career, traders who use take profit orders tend to perform better than those who use market orders, which may be an indication of quick irrational decisions by traders who place market orders. As traders progress through their career, they become better at placing market orders as indicated by the negative coefficient of -0.0596 for model (2f). This may be an indication that traders better analyse the market and place market orders in a more efficient manner.

Regarding the *Long* parameter, I report coefficients of around -0.1781, 0.04117, 0.07611, and -0.0884 for models (2c), (2d), (2e), and (2f), respectively. This shows that the *Long* parameter alternates between negative and positive coefficients. Such a pattern can be explained by the notion that the FX market is typically characterised as a random walk with no drift over the long-term, where

it is difficult to forecast the direction of the price of exchange rate in a consistent manner. Hence, it is expected that traders are not able to capture the direction of FX price movements in a consistent manner over their trading career as FX prices move in a random fashion (Pukthuanthong-Le and Thomas, 2008).

Nevertheless, this ability disappears as traders become very mature. I find a negative coefficient for the *Volume* variable for Models (2d), (2e) and (2f), which means that traders who trade larger positions tend to be less successful in future trades. This may be interpreted as sign of overconfidence, whereby traders record losses on large positions, which they were expecting would return a significant profit.

Finally, for *TradeFrequency*, I report a significantly negative coefficient of -0.0311 for Model (2c), and a small yet positive coefficient of $1.0e-5$ for Model (2f). This means that traders are less successful in the first trades they execute (i.e. just starting out their trading career). Moreover, executing more trades does not have a significant impact on traders' success rate meaning that retail traders do not improve their performance by simply executing more trades. This is similar to our earlier finding and the evidence presented in the literature. Considering an alternative interpretation of *TradeFrequency* as a proxy for overconfidence, the results show that at the start of their career, traders are less confident about their skills and tend to underperform relative to the end of their trading career, where they have gathered enough real experience and are more confident about taking risks and holding on to open losing positions until they turn into a profit. While in the literature on equities, overconfidence often results in overshooting forecasts due to interpolating recent trends too far into the future, in the context of FX

trading, overconfidence can be interpreted as a trader's ability to be comfortable with high levels of risk and not panicking and closing positions prematurely at a loss.

I repeat all the above models with *ROI* as the dependent variable, and replacing the independent variable *Career SR* with *Career ROI*, in order to investigate heterogeneity in performance based on traders' ability to add value in absolute terms. The results are presented in Table 2.1.1.2. In general, the models have weak explanatory power. Starting with Model (2a), which does not include time and trader fixed effects, I find no significant relation between *Career ROI* and *ROI*. This means that a trader's previous return on investment is not related to future returns, indicating that the ability to add value in absolute terms is not related over time. Hence, an individual who exhibits positive ROI in previous periods is not likely to exhibit similar performance in future periods. All other independent variables are statistically insignificant except for the *Duration* and *Long* variables, which are only positively statistically significant at the 90% confidence level. As such, the longer the average duration of a trade, the higher the ROI. The reason is that trades are initially opened in a net loss due to the bid-ask spread, hence, it may take some time before the price moves in favour of the trader in order to cover the bid-ask spread and generate a profit. Regarding the *Long* parameter, I find a positive coefficient meaning that traders who predominantly have long positions tend to have positive ROI on future trades. Nevertheless, given the almost zero R^2 of the model, these findings should not be given much weight in the final conclusion.

I repeat the analysis including time and trader fixed effects in Model (2b), however, the results remain largely the same. Specifically, I find not significant relation between *Career ROI* and *ROI*, meaning that performance based on this measure follows a random pattern. Again, I highlight that the R^2 of the model is almost zero, indicating poor explanatory power.

Next, I divide the data into the different phases of a trader's careers: first ($N \leq 10$), early ($10 < N \leq 25$), middle ($25 < N \leq 50$), and late ($N > 50$) trades. I repeat the analysis in order to examine the impact of *Career ROI* on future trading as a trader matures and progresses through his trading career. The results are reported in Table 2.1.1.2 under Models (2c), (2d), (2e), and (2f), respectively, for each subsample. I find that the coefficient for *Career ROI* is statistically insignificant across all models as previously found on the full set of traders. Regarding *Duration*, I find a positive coefficient in Model (2e) of $3.8e8$, which turns negative in Model (2f) with a coefficient of $-7.78e6$. This extreme shift in magnitude and sign in trade duration between traders with 25 to 50 executed trades and those with more than 50 trades shows that while traders are still maturing, they are able to generate highly positive returns the longer the trade; however, during the last phase of their career, they might have kept open some positions which have negative unrealised profits. As such, these longer duration trades are reflected by negative ROIs. With respect to limit orders, I report a positive coefficient for the *SL* variable for models (2d) and (2e), and a negative coefficient for Model (2f). This means that in the earlier phases of their trading career, traders profitably use stop-loss orders compared to market orders to limit their losses and improve their performance. As for the *TP* variable, I find a

negative coefficient for Model (2d) and positive coefficients for models (2e) and (2f), meaning that as traders mature, they tend to use take profit orders more profitably than market orders. This is opposite to the results found using the success rate performance measure; however, the R^2 of the models in the analysis based on ROI are near zero and should be taken with a grain of salt. The *Long* parameter, is reported to have a positive coefficient in Model (2d) and negative coefficients in models (2e) and (2f). As mentioned earlier, this pattern can be explained by the notion that the FX market is typically characterised as a random walk with no drift over the long-term, where it is difficult to forecast the direction of the price of exchange rate in a consistent manner. Hence, it is expected that traders are not able to capture the direction of FX price movements in a consistent manner over their trading career as FX prices move in a random fashion (Pukthuanthong-Le and Thomas, 2008). Finally, I find statistically insignificant coefficients for the *Volume* and *TradeFrequency* variables. It is very important to highlight that the R^2 of all subsample models is close to zero meaning that the models have very poor explanatory power. As such, these analyses should not be emphasised when making inferences about the relation between return on investment and trader characteristics.

As an additional investigation, I repeat the analyses above where I include both *Career SR* and *Career ROI* as independent variables for each of the dependent variables *SR* and *ROI*, and report the results in table A.1 and A.2, respectively, in the Appendix. I focus the discussion only on the covariate of interest, namely *Career SR* and *Career ROI*. Regarding the models with *SR* as the dependent variable, I find that *Career SR* has a positive and persistent effect as found in the

initial analysis. In particular, the coefficient in Model (2a) is 1.08 and grows from 0.216 in Model (2c) to 2.66 in Model (2f). This means that traders exhibit an autoregressive pattern in their ability to correctly predict future price movements, which can be interpreted as evidence of temporal heterogeneity. I find no significant relation for *Career ROI*, which means that there is no relation between a trader's historical ability to add value to an investment with their future ability to predict the direction of price changes. As such, these two skills are independent of one another.

Next, I examine the models with *ROI* as the dependent variable as presented in Table A.2. For all models, I find no significant effect for either *Career SR* or *Career ROI* on *ROI*. This result is similar to what I obtained in the initial analysis for *ROI* (i.e. no significant relation between *ROI* and *Career ROI*) and in the previous analysis between *SR* and *Career ROI*. These results imply that a trader's future ability to add value to an investment is not related to their past ability to either add value to previous investments or their past ability to predict the direction of price movements. It is important to note that the R^2 for all the models is close to zero, indicating poor model fit. Hence, these results should be considered with caution.

3.3.1.1.2 Daily Aggregated Analysis

I repeat the analysis using daily aggregated data, where the daily success rate of the trader is the average success rate on a particular trading day. The results of Model 2 and its variations are presented in Table 2.1.2.1.

The results of Model (2a) on the full sample of traders show that the career success rate of an individual is positively related to the t^{th} day success rate. This

is indicated by the statistically significant coefficient of 0.7042. Similarly, to the transaction level analysis, this suggests that some traders exhibit systematic outperformance, which can be interpreted as evidence of cross-sectional heterogeneity in performance of traders.

The mean trade duration of a trader is positively related to the t^{th} day success rate as indicated by the significant *Duration* coefficient of 3.65e-8. While this number may seem small, recall that *Duration* is measured in seconds. Hence, the longer the mean duration of trades, the higher the likelihood of achieving a high success rate. This is partially due to the fact that trades are initially opened at a loss that equals the bid-ask spread, hence it may take some time before prices move significantly in a favourable direction to cover the bid-ask spread and generate a positive profit.

Regarding limit orders, I find that the *SL* parameter has a negative coefficient of -0.0884, which suggests that traders may be selecting stop loss levels that are very close to the market price. Hence, any slight change in the price would trigger the stop loss order. It follows that traders who tend to have most of their positions closed due to stop losses may be placing suboptimal or very narrow limit levels.

I find an insignificant coefficient for the *TP* variable, which is different than the result I obtained in the transaction level analysis. This suggests that traders on average do not use take-profit orders to realise gains or place very wide limits that are not triggered, which may be due to the notion that retail traders are not consistently placing feasible take-profit levels.

With respect to the direction of a trade, I find a coefficient of -0.0615 for the *Long* parameter, which indicates that traders with relatively more long positions tend to have less successful trades. This may be an indication that these traders have strict trading strategies that prevent them from taking excessive short positions, which are considered to be riskier in general.

I find a significant coefficient of -0.0055 for the *Volume* parameter. This means that traders with larger positions historically tend to be unsuccessful in future trades, which may be a sign of overconfidence. Hence, as traders are more confident in their decisions and invest larger amounts, they may underestimate risk, resulting in losses on future trades. Note that while the coefficient is small, the *Volume* variable is measured in lots, where one lot is equivalent to 100,000 of the base currency.

Finally, for *TradeFrequency*, I report a coefficient of $1.06e-6$, which is very small and suggests that trader performance does not improve much as they execute more trades.

Model (2a) does not include time and trader fixed effects, and has an R^2 of 9.64%. In order to account for time and trader fixed effects, I repeat the same analysis on the full sample; however, I include year, month and trader fixed effects. The results of Model (2b) remain largely the same. Most importantly, the *Career SR* coefficient is 0.7016, which is very similar to what I obtained in Model (2a). This further supports the evidence of significant heterogeneity in performance among retail FX traders. I obtain similar results for all the other control variables, thus I avoid repeating the discussion. The R^2 of Model (2b) is equal to 9.73%.

Next, I divide the data into the different phases of a trader's careers: first ($N \leq 10$), early ($10 < N \leq 25$), middle ($25 < N \leq 50$), and late ($N > 50$) trades. I repeat the analysis in order to examine the impact of career success on future trading as a trader matures and progresses through his trading career. The results are reported in Table 2.1.2.1 under Models (2c), (2d), (2e), and (2f), respectively, for each subsample.

I find that the coefficient for *Career SR* is statistically significant and positive across all models, and it increases as a trader gains more experience through trading. Specifically, the coefficients for Models (2c), (2d), (2e), and (2f) are 0.25, 0.6244, 0.7433, and 0.9282, respectively, which shows that the estimated coefficient increases as a trader progresses through his trading career, since the average career success rate is estimated more accurately as the number of observations increases. This implies that heterogeneity in performance among traders persists and increases as traders progress in their trading career. My results are similar to the evidence presented by Hayley and Marsh (2016), who showed that there exists significant persistence in heterogeneity in performance among retail FX traders.

Regarding the variable *Duration*, I find a positive coefficient across all models, which may be due to the fact that trades are initially opened in a loss due to bid-ask spreads, and it takes some time before prices move favourably and generate a profit.

With respect to limit orders, I report a negative coefficient for the *SL* variable across all models, which is similar to the result on the full sample. Similarly, this means that traders may be placing stop loss levels that are very close to the

market price, such that any slight change in the price would trigger the stop loss order. Hence, this strategy would have a negative impact on the success of trades.

As for the *TP* variable, which was statistically insignificant under the full sample analysis, I find that this parameter becomes significant for Models (2c), (2d), and (2e), with coefficients of 0.0494, 0.0378, and 0.0246, respectively, but remains insignificant for Model (2f). These decreasing coefficients suggest that as traders progress in their trading careers, they use take profit orders less efficiently.

Regarding the *Long* parameter for the four models, I report coefficients of around -0.0393, 0.0111, 0.0177, and -0.007, respectively. This suggests that during their early trading career, traders tend to execute unsuccessful long positions; however, as they progress in their trading career they become more successful in placing long positions. Nevertheless, this ability disappears as traders become very mature, which again is consistent with the evidence in the literature (Hayley and Marsh, 2016) that retail FX traders do not improve their performance over time. I find a negative coefficient for the *Volume* variable for Models (2d), (2e) and (2f), which means that traders who trade larger positions tend to be less successful in future trades. This may be interpreted as sign of overconfidence, whereby traders record losses on large positions, which they were expecting would return a significant profit.

Finally, regarding *TradeFrequency*, I report a significantly negative coefficient of -0.0054 for Model (2c), and a positive yet very small coefficient of $7.09e-7$ for Model (2f). This means that traders are less successful in the first trades they

execute (i.e. just starting out their trading career); moreover, they do not learn to improve their performance by a significant amount as they execute more trades.

I repeat the above analyses using *ROI* and *Career ROI* instead of *SR* and *Career SR*, respectively, and I present the results in Table 2.1.2.2. In general, all models have very poor explanatory power, thus I will not go into too much detail about the results since they are mostly statistically insignificant. I find that *Career ROI* does not have any significant effect on ROI. As in transaction level analysis, this implies that previous return on investment is not related to the return of future trades, meaning that ROI is random over the career of a trader. All other independent variables are generally statistically insignificant except for *Duration* and the *Long* parameters. Specifically, the longer the average duration of a trade, the higher the ROI. This is because trades are initially opened in a net loss due to the bid-ask spread, hence, it may take some time before the price moves in favour of the trader in order to cover the bid-ask spread and generate a profit. As for the *Long* parameter, I find a positive coefficient meaning that traders who predominantly have long positions tend to have positive ROI on future trades. It is important to mention that, given the almost zero R^2 of the models, these findings should not be given much weight in the investigation of the effect of trader characteristics on ROI.

As a robustness check, I repeat the above analyses on a dichotomised version of the daily success rate, such that $SR_{i,t}$ equals one if the daily aggregated success rate is greater than 50%, and zero otherwise. The results are reported in Table 2.1.3.1. In general, the results obtained for all models are similar to my previous results; hence I keep the discussion brief in order to avoid repetition. I

find significant evidence of heterogeneity in performance, which increases as traders progress in their trading career. Specifically, the coefficient for *Career Success* is 0.1812 for Model (2c) and increases to 2.6751 in Model (2f). The *Duration* variable is found to be positively related to the daily success rate, which is similar to what I found in the previous analyses. *SL* has a negative impact on success, while *TP* is found to be positively related to it. The *Long* and *Volume* variables are negatively related to the future daily success rate, while *TradeFrequency* is positively related to it in general. Similar to the previous transaction level analysis, *TradeFrequency* as a proxy for overconfidence shows that as traders progress through their careers, they become more confident and comfortable with taking on more risk. As such, as traders become more confident, their success rate improves.

When using *ROI* and *Career ROI* instead of *SR* and *Career SR*, respectively, in the dichotomised version of the daily aggregated data, I find no significant effect of *Career ROI* on *ROI* for the full sample even after accounting for both time and trader FE. I only find significant but very small coefficients for models (2d) and (2f). In general, the results from the dichotomised version of the daily aggregated data support my earlier findings, that there is no significant relation between an individual's previous return on investment and their ability to add return in the future.

3.3.1.1.3 Data Winsorisation

As another robustness check, I winsorise the data by taking the middle 95%, 90%, 85%, and 80% of observations based on the *SR* and *ROI* variables depending on the covariate of interest. In general, the results do not vary much

from the full sample analysis, and in order to avoid repetition I only report in the appendix the results for the 90% winsorisation. Moreover, since the conclusions are the same as previously mentioned I keep the discussion brief. The results for the transaction level logistic model are presented in Table A.3 in the appendix, and show that for the full sample, even after accounting for both time and trader fixed effects, there is a positive relation between *Career SR* and *SR*. This suggests a positive relation a trader's historical ability to correctly predict the direction of prices, and his future ability to do so. Moreover, there is persistence in this relation as shown in models (2c), (2d), (2e), and (2f), where the *Career SR* coefficient grows as a trader matures.

When I consider the *ROI* parameter at the transaction level (Table A.4), I do not find any significant relation with *Career ROI* as in the full sample analysis. This suggests that there is no relation between an individual's historical ability to add value to an investment and his future ability to do so.

Next, I aggregate the data on a daily basis and repeat the analyses using a linear model. The results for *SR* and *ROI* are presented in tables A.5 and A.6, respectively. As in previous analyses, I find only a significant positive and persistent relation between the *Career SR* and *SR*, and no significant relation between *Career ROI* and *ROI*.

When I dichotomise the daily data and use the logistic model, I find significant results for both *SR* and *ROI*. Specifically, Table A.7 shows a significant positive and persistent relation between *Career SR* and *SR* as I found in previous analyses. However, I also find a positive relation between *Career ROI* and *ROI* which suggests that a trader who has generated positive (negative) *ROI* in the

past is likely to generate positive (negative) ROI on future trades. When looking at the subsample analyses, I find that the *Career ROI* coefficient decreases as a trader progresses through his career. This means that the relation between past and future ability to generate returns decays over time. One explanation is that the coefficient in model (2f) is a more accurate representation of such a relation since it is estimated using a subsample of traders who have more than 51 trades. Hence, the parameter is more robust and representative. An alternative explanation is that the relation between past and future ROI decays as a trader progresses through his trading career. As such, a trader's performance converges towards a more random pattern, where historical performance is not indicative of an individual's future abilities. It is important to note that the R^2 of all models in Table A.8 are very small indicating a poor model fit, thus all results and conclusions should be considered with a grain of salt.

As mentioned at the start of this section, while I only report the results for 90% winsorisation, the results obtained for the 85%, and 80% winsorisations are very similar, hence I avoid repetition.

3.3.1.1.4 Discussions on Heterogeneity in Trader Performance

The key finding of the above analyses is that there is significant cross-sectional heterogeneity in the performance of traders, which confirms the results of Abbey and Doukas (2014) and Haley and Marsh (2016). Moreover, my findings highlight that persistence in heterogeneity is consistent and increases as individuals' progress in their trading careers.

The study of Hayley and Marsh (2016) is limited to the trader's activity on an aggregated daily level. Hence, the data used in their study only shows the final trading outcome of the day and ignores any intraday variation in trader performance. Moreover, their data is limited in the number of control variables available. As a result, their model does not allow us to examine heterogeneity at the transaction level, as I do in my initial analysis, or control for trading characteristics which can affect performance.

This is the first study that allows us to examine heterogeneity in performance at the transaction level and control for other factors, which may affect the ability of a trader to place successful trades. This research goes beyond the effect of learning on trader performance by investigating how a trader's success rate is influenced by their average *Duration*, *SL*, *TP*, *Long*, *Volume* and *TradeFrequency*. My findings contribute to the literature of heterogeneity among retail FX traders by showing that trade specific characteristics have a significant impact on heterogeneity in performance.

Hence, high levels of heterogeneity validate the argument that traders in the retail EUR/USD FX market perform differently mostly due to various trading strategies such as short-term and long-term and different levels of expectations.

In addition, during any given trading day, trader decisions differ based on the direction of the EUR/USD spot rate, the duration of the price trend and the peaks and troughs in price movements. It follows that heterogeneity in performance arises from these different trader beliefs and that this heterogeneity is consistent throughout an individual's trading career. This brings me to the second methodology to test for heterogeneity of trader expectations.

3.3.1.2 Heterogeneity of Trader Expectations of Spot Prices

The results of both equation (2.3) and equation (2.4) are presented in Table 2.2. Starting with the full sample of traders, I estimate equation (2.3) and find significant evidence of heterogeneous expectations.

Specifically, using a 95% confidence level, around 60% of traders are found to have heterogeneous beliefs of what spot EUR/USD prices should be. This percentage drops to 55% when I use a 99% confidence level. I argue that this is not due to asymmetric information held by traders, but rather due to the different trading models and indicators adopted. This is because information in the foreign exchange market is highly likely to be publicly disclosed and common to all participants, as contrasted to the equity market where there is a higher likelihood of asymmetric information resulting from private analyst reports or even insider information.

With respect to equation (2.4), which accounts for idiosyncratic effects, the analysis on the full sample of traders shows that around 53% of traders have heterogeneous expectations. This is similar to my initial finding. Moreover, I find that between 4% and 6% of traders have only a significant idiosyncratic coefficient. Given the assumption that there is no information asymmetry in the EUR/USD market, the results suggest that these traders use different forecasting models with at least a two-period lag. Excluding these variables may bias the estimation of as indicated by the small drop in the number of individual effects reported for equations 2.3 and 2.4. Finally, I find that between 7% and 16% of traders exhibit both individual as well as idiosyncratic effects, meaning that these

individuals, not only incorporate lagged information into their models, but also have significantly unique expectations of the EUR/USD spot price.

The full sample of traders includes individuals who have very few trades. Thus, analysing the uniqueness of their expectations with only a few observations can result in misleading inferences. In order to remedy this, I re-estimate equations (2.3) and (2.4) on a sample of traders with a trading frequency greater than 30 trades (see Table 2.2). The results of equation (2.3) show that around 70% of traders have heterogeneous expectations when using a confidence level of 95%, and that this figure drops to 65% at the 99% confidence level. These results further support my argument that retail foreign exchange traders in the EUR/USD market have different expectations of spot prices.

As for the results of equation 2.4 on the limited sample of traders, I find that around 60% of traders have a significant individual effect, suggesting that a large portion of the sample has heterogeneous expectations. In addition, I find that between 4% and 7% of traders have a significant idiosyncratic effect, which is similar to the finding in the analysis on the full sample. Finally, I find that between 9% and 20% of traders exhibit both individual as well as idiosyncratic effects. This indicates that these traders use lagged market information in their models, as well as have significantly different expectations of the EUR/USD spot price. This may be due to traders adopting different technical indicators or having different expectations regarding how fundamental announcements and news will affect prices.

3.3.1.2.1 Discussions on Heterogeneity in Trader Expectations

Testing for heterogeneity in expectations allowed me to examine individual trading biases and validate the hypothesis that traders do not interpret public information in the same way. The high levels of heterogeneity show that traders stick in their own interpretation of information and continue to develop same routines, trading rules for their own trading style.

The high level of details available in the dataset employed in this study allows me to model to exploit the information available at the transaction level of retail FX traders. Moreover, I use the model proposed by Ito (1990), which is a simple robust test that has been widely used in literature also applied by MacDonald and Marsh (1996), Elliott and Ito (1999) and Bénassy-Quéré et al. (2003), at the institutional level in order to examine heterogeneity in expectations, which has not been investigated before at the retail level in FX markets.

My findings show that while traders receive the same set of information they interpreted it differently thus resulting in different forecasts of the future FX spot rate. This shows that an individual's biases and characteristics influence their trading decisions resulting in their forecast to deviate significantly from the general market consensus. These findings echo my previous results on heterogeneity in performance and the evidence in the literature on heterogeneity in expectations.

Given the significant evidence on heterogeneity among retail FX traders, I use the three performance measures presented in the methodology in order to identify

traders with consistent trading skills, the ability to generate positive returns, and those with big hit ability.

3.3.2 Identifying Skilled Traders

3.3.2.1 Success Ratio - Consistent Trading Skill

I find that the mean and median of the Success Ratio (SR) across traders are 59.59% and 61.33% respectively. This suggests that, on average, individual currency traders possess the ability to trade in a consistent manner by correctly forecasting future price changes (i.e. on average, traders have a $SR > 50\%$). It is important to note that while traders profitably execute more than half of their trades, this does not mean that the sum of profits and losses is positive. As such, a trader may lose a significant amount after a series of small wins, which would result in an aggregated loss over all trades.

Next, I transform the *SR* of each trader into a binary variable, which takes the value of 1 if the *Success Ratio* is significantly greater than 50% and 0 otherwise. Accordingly, I find that around 68% of traders in my sample can correctly predict future price changes more than half of the time.

Since some traders in my sample may have very few past trades this can result in extreme values for the *SR* ratio which may not be representative of trader's true skill. As such, I recalculate the *Success Ratio* by progressively increasing the restriction on the number of trades executed by each trader from 1 to 30 trades. The results remain relatively the same where a restriction of 30 trades results in an *SR* mean of 63.65% and a median of 64.35%. If I transform each trader into a binary variable as above I find that 77.8% of trader can correctly

predict future price change more than half of the time. This shows that the results are consistent regardless of the trade restriction used meaning that currency traders do possess some degree of skill, such that they are able to forecast future price movements as indicated by the aggregated mean success rate which significantly exceeds 50%.

While the success rate only takes into account the number of successful trades it does not capture the dollar value of the profit or loss. To illustrate this point, consider a trader who has executed 9 successful trades with 1 dollar profit in each of these trades, and 1 losing trade with a loss of 10 dollars. While the success rate indicates us that this individual is skilled in forecasting future prices, the total realised profit, in this case loss shows that this individual does not add value in absolute terms. Moreover, the success rate does not factor in the size of the trader's wealth. As such, a one dollar profit for a trader with a ten dollar total wealth implies a larger return compared to a similar gain for a trader with a 100-dollar account. These two drawbacks bring me to the next measure, return on investment which captures the size or the gain generated by the trader relative to his wealth.

3.3.2.2 Return on Investment (ROI) - Ability to Generate Positive Returns

The data I use in this thesis includes client balances, which allows me to calculate the return of investment for each trader. This information provides an advantage over previous studies (Haley and Marsh, 2016), which do not have access to detailed balance information. I calculate the *ROI* of each trader and find that the mean *ROI* across all traders in my sample is -28.88%, which suggests that traders lose money on average over their trading career.

This is a very interesting finding because, while 77.8% of traders are able to correctly forecast the direction of future price movements more than half of the time, they are not able to profitably capitalise on this skill. This may be due to traders recording greater losses on unsuccessful trades compared to the profits on successful positions due to undisciplined trading and poor risk management. In other words, traders use suboptimal trading rules for profitable positions relative to losing ones, which may be an indication of the disposition effect.

Next, I transform the *ROI* of each trader into a binary variable, which takes the value of 1 if the *ROI* has a positive value, and 0 otherwise. This indicates whether a trader has added value to the initial investment. I find that only around 22.8% of traders possess the skill to generate positive returns, which add value to the initial investment.

This shows that very few traders possess the ability to add value in an investment in absolute terms which is a striking difference compared to the average success rate of trades in my sample. Consequently, this suggests that while traders may be able to generate small positive returns on many trades their overall profitability is negative due to large losses on few trades, which leads them to lose money over time.

3.3.2.3 Big Hit Ability (BHA)

Success ratio and *ROI* do not take into account the size of the trade. For example, some traders based on their strategies and rules often make many small losses but in different market conditions can make few very large profits. This case will result in a low *Success Ratio* but would still be a profitable trader. In order to

measure this ability, I examine the profitability as a function of trade size and test for “big hit ability”. This will show if a retail FX trader is able to time the EUR/USD market and capitalise on opportunities by increasing his position size when the price moves favourably.

Finally, with respect to *BHA*, I find that the mean *BHA* across all traders obtained from estimating equation (1.3) is -0.087. This means that, on average, retail FX traders have negative big hit ability, which suggests that most of the traders’ large positions result in losses and most of their small positions are winners. As a result, FX traders do not possess the ability to profitably increase their exposure to large price swings.

Next, I dichotomise the *BHA* variable such that it takes the value of 1 if $BHA > 0$ and 0 if $BHA \leq 0$. I find that only around 27% of traders possess positive big hit ability. Consequently, this means that the majority of traders have negative (or no) *BHA*, which suggests that these traders are more likely to increase their position size when they are on the wrong side of the market. This result complements the finding obtained for *ROI*, where I show that 77.2% of traders have a negative return on investment. As such, my findings show that traders not only lose money over time, but also have a tendency to be overconfident when their forecast of FX rate is wrong both in terms of direction and magnitude.

3.3.3 Examining the Impact of Market Volatility on Skill

3.3.3.1 Impact of Market Volatility on Performance - Transaction Level

I begin by examining the impact of market volatility on a trader’s ability to correctly predict future price changes, which is represented by the success rate at the

transaction level. The results of Model (3.1) and its variations are presented in Table 3.1. For all models, the results obtained for the control variables are largely the same as for Model (2). Specifically, I find that *Career SR* has a positive impact on the current prediction of a trader, which suggests that traders with a better success rate reputation have a higher likelihood of correctly predicting future price changes. I find a positive coefficient for *Duration*, which indicates that traders with longer average trade durations have a better probability of executing profitable future trades. Regarding limit orders, I find a negative coefficient for *SL*, meaning that traders may be placing stop loss levels that are very close to the market price, where any small change in the price would trigger the stop loss order. This would have a negative effect on the success rate of future trades. As for the *TP* variable, I also find a negative effect of the success rate of the trade. The *Long* variable has a negative coefficient, indicating that traders tend to be less profitable in their long position compared to their short positions. I report a negative coefficient for *Volume*, suggesting that traders who trade larger positions tend to be less successful in future trades, which may be a sign of overconfidence. With respect to *TradeFrequency*, I report a positive but very small coefficient, which does not represent any significant increase in performance as individuals trade more.

Finally, with respect to *Volatility*, I find that the volatility on the day the position was opened has a negative effect on the prediction of the trader across all models. This suggests that traders cannot gauge how the market will move given the uncertainty in the current period. For the lagged volatility values in Model (3.1.a), I report several positive coefficients, indicating that traders are able to use

information about past daily volatilities to correctly predict future price changes. This may be due to traders adopting stochastic volatility models or technical indicators that are based on volatility measures, such as Parabolic SAR (Stop And Reverse) and Bollinger Bands, typically provided by the trading platform.

Next, I estimate three models, Model (3.1.b), Model (3.1.c), and Model (3.1.d), such that Volatility is a dummy variable that takes the value of one if the volatility on that day is greater than the 70th, 80th, and 90th percentiles over the past 30 days, respectively. This allows me to examine how heightened market volatility affects trader skill. Model (3.1.b) shows that high volatility in the most recent trading days (i.e. up to a lag of three trading days) has a generally negative effect on a trader's predictive ability, while the volatility in earlier periods has a positive effect or a smaller negative effect. This means that traders have a harder time understanding the more recent uncertainty in the market relative to the events that have become seasoned for several days. Model (3.1.c) presents similar results in that the high volatility in the most recent periods has a negative effect on trader predictive ability. As for Model (3.1.d), the results show additional evidence that when volatility is high, a trader's predictive ability perishes. This is shown by the predominantly negative coefficients for the volatility lags.

3.3.3.2 Discussions on Market Volatility on Trader Skills

I expand on the model proposed by Haley and Marsh (2016) by including a dynamic autoregressive variable on market volatility in order to examine the effect of heightened market volatility on trader skill.

In general, the results show that individual traders are unable to predict future price movements when uncertainty in the market is high. This may be due to the lack of accurate information in times of market turbulence, coupled with individual biases such as fear, which may drive traders to open positions based on sentiment and their own personal gut, rather than sound economic or fundamental analysis. As such the high volatility in the market leads to irrational trading behaviour, which negatively affects the ability of traders to correctly forecast the direction of future price changes.

In addition, I find that as market volatility becomes dated it starts to have a lesser impact on trader skills as indicated by the decreasing higher-order volatility lags. This indicates that traders adjust to high market volatility over time. My findings are similar to those found in the literature on volatility (Olson, 2004; Qi and Wu, 2006), which shows that volatility has a negative effect on performance.

3.3.3.3 Impact of Market Volatility on Return of Investment

Next, I fit Model (3.2) and its variations in order to examine how market volatility impacts the *ROI* of traders. The results are presented in Table 3.2. In general, all the models have a very poor fit as indicated by the low R^2 , and almost all the parameters are statistically insignificant. I find that *Career ROI* is insignificant which suggest that past performance is not associated with a trader's future *ROI*. This suggests that traders do not learn to trade better in terms of adding value to their investment. The variable *Duration* has a positive effect on the *ROI*, meaning that it takes a longer period of time for a trade to turn profit. As for the *Long* variable, I also find a positive effect, which suggests that traders tend to close position with a profit more often when the position is long compared to short

positions. Finally, regarding *Volatility*, I find a generally negative relation with a trader's *ROI*, specifically at lags of 4 and 10 trading days. While this evidence is weaker compared to the results obtained when using the success rate, the results still indicate that high market volatility negatively impacts a trader's ability to add value in absolute terms. Nevertheless, given the poor fit of the model and the largely insignificant coefficients, the results of Model (3.2) should be interpreted with caution.

3.3.3.4 Impact of Market Volatility on Performance - Daily Level

As a robustness check, I repeat the analysis done for the success rate; however, I use daily aggregated data. The results are presented in Table 3.3. In general, the results obtained for all models are similar to those obtained using the transaction level data, hence I briefly discuss the results to avoid repetition.

For all models, the results obtained for the control variables are largely the same as those obtained in the heterogeneity analysis. In particular, *Career SR* has a positive impact on the current prediction of a trader, which implies that traders with a good success rate history have a higher likelihood of correctly predicting future price changes. The other control variables also have similar coefficients; thus I do not discuss them here.

As for *Volatility*, I find that the aggregate success rate on a given day is negatively affected by the volatility on that day. This means that traders cannot make sense of the uncertainty in the current period. Regarding the lagged volatility values in Model (3.3.a), I report several positive coefficients as in Model (3.1.a), indicating that traders are able to use information about past daily volatilities to correctly

predict future price movements. Models (3.3.b) and (3.3.c) show that high volatility in the most recent trading days (up to a lag of three trading days) has a generally negative effect on a trader's predictive ability, while the volatility in earlier periods has a generally positive effect. This means that traders have a harder time understanding the more recent uncertainty in the market relative to the events that have become seasoned for several days. As for Model (3.3.d), the results indicate that when volatility is high, a trader's predictive ability declines.

3.3.4 The Impact of Behavioural Biases on Trader Skill

The results of the regressions showing the impact of a trader's behavioural biases on skill are presented in Table 4.

3.3.4.1 Impact of Behavioural Biases on the Ability to Successfully Predict Future Price Movements

I begin by examining the effect of a traders' behavioural biases on their ability to successfully predict future price movement, which is measured by the Success Ratio (SR). Starting with the herd initiations indicator, *HERD*, I find that traders who initiate herds tend to correctly predict future price changes as indicated by the positive coefficient in both Model (4.1) and Model (4.2). This means that these trade leaders attract followers or copiers due to their ability to correctly forecast the direction of future price changes. Regarding the disposition effect (DISP), I also find a positive coefficient of 0.213 for Model (4.1) and a coefficient of 1.37 for Model (4.2). This suggests that traders who have a higher tendency to close winning positions compared to losing ones, have a higher *SR*. This finding is

logical since traders who close more winning positions, will have a higher proportion of trades that are successful. As such, one would expect to find a positive relation between the *SR* and the *DISP* indicators. Next, I investigate the sensation seeking behaviour of traders and find that traders who use more leverage or who have a higher margin utilisation (*MU*) tend to have a higher *SR*; however, this result is only obtained for Model (4.1) with a positive but small coefficient of 0.006. Thus, traders who use more margin are able to exploit small price swings, which allows them to close positions once the trade is winning. Nevertheless, it is important to note that this coefficient is relatively small, hence traders who use more leverage are likely to increase their success rate only by a small percentage.

I also use the squared margin utilisation (MU^2) in order to capture the non-linear relation between margin utilisation and *SR*. I find a negative yet very small coefficient of around -0.0001 for Model (4.1) and -0.001 for Model (4.2), which suggest a concave relation between margin utilisation and success rate, where very high levels of margin utilisation have an unfavourable impact on the *SR* of a trader. This is because, as positions become extremely leveraged, adverse price movements can quickly exhaust a trader's margin, triggering a margin call and consequently forcing the trader to close the position in a loss. As higher levels of leverage are used, a trader would start accumulating losing trades, which would negatively impact the *SR*. With respect to inconsistent behaviour (*INCON*), I find a positive but extremely small effect for both Model (4.1) and Model (4.2) with coefficients of $3.7e-7$ and $1.8e-5$, respectively. This means that traders who vary their margin utilisation levels are more likely to have a very small increase in *SR*;

however this impact is almost insignificant and can be ignored. Finally, for the information advantage indicator, I find negative coefficients of $-2.6e-6$ and $-2.9e-5$ for Model (4.1) and Model (4.2), respectively. This means that, the greater the time it takes a trader to cover the spread cost after opening a position, the less informed they are, and the lower their *SR*. In other words, traders who do not have an information advantage are less likely to have a high number of successful trades. The R^2 and pseudo R^2 of Model (4.1) and Model (4.2) are 29.82% and 18.66%, respectively, indicating a good model fit.

3.3.4.2 Impact of Behavioural Biases on the Ability to Add Absolute Value on Investing

Next, I investigate the impact of behavioural biases on *ROI*. The *HERD* variable has a positive effect on *ROI* with coefficients of around 0.0004 and 0.007 for Model (4.1) and Model (4.2), respectively. This means that these trade leaders can add value to an investment through positive *ROI*. However, the small values of this coefficient show that this added value is really small which implies that it is very challenging to be a trade leader in market that is categorised in the literature as a random walk. Regarding the *DISP* variable, I obtain a negative coefficient of -0.046 for Model (4.1), which may be due to traders realising many positive but small profits and some significant losses. The result obtained for Model (4.2) is different, with a positive coefficient of 0.417, suggesting that the disposition effect (i.e. greater tendency to realise gains compared to losses) increases the likelihood of having a positive *ROI* in absolute terms. Moreover, I find that there is a positive relation between sensation seeking (*MU*) and *ROI* as indicated by the positive coefficients of 0.034 and 0.119 for Model (4.1) and Model

(4.2), respectively. This suggests that the greater the leverage used by the trader, the higher the *ROI*. Nevertheless, this relation is concave, such that extreme levels of leverage have a detrimental impact on *ROI*. Finally, I find a positive relation for the *INCON* indicator in the two models. This indicates that traders who use different leverage levels have higher *ROI*, which may be a sign of the trader's ability to adjust risk-appetite depending on market conditions. The R^2 and pseudo R^2 of Model (4.1) and Model (4.2) are 3.35% and 5.11%, respectively.

3.3.4.3 Impact of Behavioural Biases on the Ability that Retail FX Traders Adjust the Size of their Position Based on their Confidence in their Forecast

In the third analysis, I investigate the impact of behavioural biases on the trader's *BHA*. The *HERD* indicator is found to have a positive effect on *BHA* with coefficients of around 0.0004 and 0.004 for Model (4.1) and Model (4.2), respectively. This means that trade leaders possess *BHA* such that they trade a larger volume when they are more confident in their trading decision. The small values of this coefficient may be due to the fact that very few traders have a high *BHA* in absolute value. For the *DISP* variable, I only find a positive effect for Model (4.1) with a coefficient of 0.035, meaning that traders who exhibit the disposition effect also tend to have *BHA*. With respect to sensation seeking, I report positive coefficients of 0.01 and 0.049 for Model (4.1) and Model (4.2), respectively. This suggests that traders who use high levels of leverage possess *BHA*, such that the volume of the trade with the leverage accounted for is high when the trader is most confident in his decision. Nevertheless, this relation is concave as indicated by the negative coefficients of the MU^2 variable. Finally, I find positive

coefficients for the *INCON* variable for the two models, which suggests that traders use different leverage and risk levels depending on the market state. This result is consistent with individuals who possess *BHA*, since *BHA* signifies a trader who is able to adjust the amount invested depending on his confidence in the market. The R^2 and pseudo R^2 of Model (4.1) and Model (4.2) are 1.74% and 1.96%, respectively, which suggest a poor model fit.

3.3.4.4 Discussions on the Effect of Behavioural Biases on Trader Skills

In general, I find that skilled traders, regardless of the skill measure used, are 1) herd initiators, 2) exhibit the disposition effect, 3) are sensation seekers, 4) exhibit inconsistent behaviour and 5) do not have an information advantage.

With respect to herd initiations, it is reasonable that skilled traders lead the herd since part of their ability to consistently predict future prices changes is their tendency to invest before others recognise the potential profitable opportunities. As such these individuals are leading others and benefiting from the momentum created by the herding effect.

Regarding the disposition effect, skilled traders are more likely to realise profits compared to losses, which inherently increases the success rate of the trader. This is because as traders realise gains and wait for losing positions to turn into a profit, the proportion of successful trades realised by the trader increases, which translates into a disposition effect. While these skilled traders secure a certain level of profit they may be closing these winning trades prematurely, hence they are not realising the full potential of their trading decisions.

Thirdly, I find that skilled traders are sensation seekers which means that these individuals search for thrilling opportunities which in turn result in successful and profitable investments. This implies that skilled traders have a certain high level of risk appetite and the desire to explore uncharted avenues in terms of trading strategies in order to stay ahead of the game.

Fourthly I find that skilful traders exhibit inconsistent behaviour which implies that these individuals change their risk exposure and trading strategies depending on their confidence in their decisions and the state of the market. In other words, these individuals are active traders who are dynamically changing their trading behaviour in order to adjust to constantly changing market environments.

Finally, with respect to information advantage I find no evidence that skilled traders possess any superior fundamental information about foreign exchange rates. This implies that their skill is not derived from private information but rather from their ability to gauge the direction of future price movements, which may be due to their use of strategies, such as momentum, that are driven by short-term market trends.

A key limitation of this analysis is the limited number of behavioural proxies used to explain the attributes of skilled traders. While the list of proxies I used is not comprehensive of all potential behavioural factors that may influence the skills of a trader, I created this list based on the most popular biases that have been investigated in the literature and it presents a starting point for us to understand some of the characteristics of skilled traders. The reason I use a limited set of behavioural biases is due to the significant computational power and time required to compute these proxies for all traders in my sample. At the time of

starting this analysis computational power was limited and expensive. However, as cloud computing becomes more efficient and affordable, I aim to expand my study to include additional biases. Moreover, I plan to use different variations of these behavioural proxies for robustness checks.

Section 4. Conclusion and Future Work

4.1 Conclusion

In general, this thesis investigates the performance and behaviour of retail FX traders, which is an area that has not been intensely explored by academics due to limited access to high quality, detailed data.

I first began by examining heterogeneity among 21,300 retail FX traders in the EUR/USD market. Using popular empirical methods such as those employed by Hayley and Marsh (2016), and Ito (1990), I found significant evidence of heterogeneity in expectations of future spot prices and in performance among traders. Moreover, I found that persistence in heterogeneity increases as traders progress in their trading career.

The evidence presented on heterogeneity among traders raises the question of whether some individuals possess genuine skill. In other words, do some traders have the ability to consistently and correctly predict future price changes in the foreign exchange market, and generate positive returns?

Hence, the second part of my analysis examined the skills of these retail FX traders. I used three performance measures; success ratio (SR), return on investment (ROI), and big hit ability (BHA). In general, I found that although around 68% of traders have the ability to consistently predict future price changes more than half of the time, only 22.8% of them possess the skill to generate positive total returns as suggested by their ROI. In addition, the average ROI across all traders is -28.8%, which indicates that retail FX traders lose money on

average. This may be due to the random nature of the EUR/USD market which consequently implies random performance, and the latter coupled with spreads can result in negative performance among traders. Finally, regarding BHA, I found that traders exhibit negative BHA on average, with only 27% of traders showing positive BHA. This implies that the majority of individual traders do not have the ability to favourably increase their position size when the market is in line with their forecast.

An important factor that affects the performance of traders is market volatility. Hence, I examined how market volatility impacts the ability of traders to correctly predict future price changes as well as their ability to add value to an investment. I estimated a series of models where I examined the effect of volatility on the day a position was opened, in addition to the lagged volatility of the previous 10 trading days on the success and the ROI of traders on each trading day. I also used binary volatility parameters to investigate the impact of high market uncertainty on traders' abilities.

Overall, I found that traders are unable to correctly incorporate recent market uncertainty in their predictions. Nevertheless, as these high volatility events become seasoned for several days, traders are better able to use and understand them in order to forecast future price changes. In addition, I found that high market uncertainty has a detrimental impact on a trader's ability to predict future price changes. The latter may be due to lack of good quality information during times of market turbulence and to behavioural biases such as fear, which drives individuals to make decisions based on sentiment rather than sound economic judgment.

Regarding the impact of volatility on the traders' ability to generate positive returns, the models have a poor fit and most parameters are statistically insignificant. However, I found some evidence that high market volatility has a negative effect on a trader's ability to generate positive returns.

In general, I found significant evidence showing that (high) market volatility is detrimental to both a trader's ability to predict future price movements and to his ability to add economic value to an investment.

I examined the relationship among five behavioural biases, which are herd initiations, the disposition effect, sensation seeking, inconsistent behaviour, and information advantage and the skills of traders, as measured by three performance metrics: Success Ratio (SR), Return on Investment (ROI), and Big Hit Ability (BHA). Generally, I found that traders who possess all three skills are herd initiators, hence they are closely watched and copied by other traders. I found that skilled traders also exhibit the disposition effect, whereby they are more likely to realise small gains and hold on to large losses. This can be interpreted as a beckoning mechanism such that these traders realise many small gains to signal to others that they possess superior trading skills. Skilled traders are also sensation seekers, indicating that they tend to use leverage to exploit price changes. Nevertheless, they tend to avoid extreme leverage levels, which can be detrimental to their performance and reputation. In addition, skilled traders are more likely to be inconsistent in the amount of leverage and margin they use. This is explained as the skilled traders' ability to adjust the amount of leverage used depending on the state of the market and their confidence in their decisions. Finally, I showed that traders who have high SR tend to execute trades that

quickly move into-the-money, while those with low SR tend to have longer trade durations before the trade covers the spread cost.

4.2 Contribution

This thesis sheds light on the characteristics of retail foreign exchange traders. My findings showed that heterogeneity is a constant and significant feature of the foreign exchange market where retail traders exhibit differences in trading performance and expectations of the future exchange rates. This challenges traditional financial theory, which postulates that market participants are homogenous and should have the same expectations of asset returns. As such, I showed that heterogeneity is in fact a feature of the market and should be examined and incorporated into pricing and forecasting models in order to capture the dynamics of the retail FX market.

With respect to the skills of retail FX traders, my findings contribute to the literature by showing that individual retail FX traders do not generate positive absolute returns on average over their trading career despite the fact that the majority of retail FX traders can forecast price movements correctly more than half of the time. It is important for retail traders to be aware of these typical performance patterns so that they are able to better manage their expectations when trading in the foreign exchange market. The sooner they understand that exchange rates move in a random fashion and that any predictive power their models may have are likely to be short-lived, the better they will become at managing their risk and adopting dynamic decision-making processes that factor in changes in the state of the market.

My thesis also highlights the importance of accounting for market volatility when making trading decisions, using a novel approach which incorporates market volatility to explain trader performance. While a chaotic market may provide many potentially profitable opportunities, retail FX traders should understand that heightened market volatility can have a detrimental impact on performance. As such, they should be constantly aware what the current state of the market volatility is in order to be able to better manage their risk and expectations of exchange rates. Moreover, looking at past market volatility may provide valuable information for traders to gauge the future volatility of the market, which would help them make more prudent financial decisions.

The final contribution of my thesis sheds light on the behavioural biases of skilled traders and how they impact performance using a novel approach. To the best of my knowledge this is the first study that investigates multiple behavioural biases simultaneously in the context of retail FX traders. I show that common behaviour biases such as herd initiations, disposition effect, sensation seeking, inconsistent behaviour, and information advantage can explain whether certain traders possess superior ability. Hence, by understanding these behavioural biases and how they affect performance, individual traders can learn to be aware of whether they are likely to exhibit these biases and take precautionary measures to avoid succumbing to the negative effects associated with them. For example, traders exhibit the disposition effect when they realise small gains and hold on to losses. A trader who realises this can learn to avoid closing winning positions prematurely and limit their losses using stop loss orders. These behavioural patterns can also be used from a broker's perspective in order to distinguish and categorise clients

into different behavioural groups in order to hedge against those who are likely top performers based on their behavioural characteristics.

In summary, this thesis highlights the uniqueness of individual retail FX traders and calls for future work to further investigate the different attributes and behavioural characteristics that shape the retail foreign exchange market.

4.3 Limitations of this Thesis

The scope of this thesis is limited by the data that was made available to me. Specifically, the data I obtained from the anonymous foreign exchange broker was only related to the EUR/USD market. As such, all my findings are specific to that market; however, due to the lack of literature that indicates variation in performance and behavioural patterns in other cross-rates, it is reasonable to assume that my findings and conclusion apply to other currency markets. The reason is because currencies are interlinked together such that the flight of cash out of one currency will most likely be exchanged into another. This relation is governed by economic theories such as purchase power parity (Cassel, 1916) and interest rate parity (Keynes, 1923). Hence, any activity in one currency will likely have an effect of similar magnitude (although of opposite direction) in another currency. However, there are several other factors which may affect this relationship regarding exotic currencies, including liquidity, spreads, and government policies. One can expect that with wider spreads, lower liquidity, and stricter government policies, a trader's performance is likely to be lower, unless the trader's skill is a specialisation in these factors such that the trader can add value by trading on these inefficiencies. In general, we can expect to find results similar to those presented in this thesis in other major currency pairs including

but not limited to GBP/USD, USD/JPY, CHF/USD, among others. It is important to note that at the time of obtaining the dataset used in this thesis, the broker mentioned that around 70% of all trading volume was conducted in the EUR/USD pair. While my analyses are yet to be conducted on other currencies to obtain empirical evidence, it is safe to say that my conclusions are related to a significant portion of trading activities in the FX market.

The second limitation of my data is that I did not have access to detailed demographic data about traders in my sample. Hence, I was unable to control for demographic factors such as gender, age, location, education, among others.

A third limitation of this thesis, and specifically related to the analysis of trader behavioural biases, is that I used a limited set of behavioural biases to explain the characteristics of skilled traders. While this list is far from comprehensive, it serves as a base to better understand the attributes of skilled traders. One reason I used a limited set of biases is due to the significant computational power and time required to calculate these parameters for all traders in my sample. However, with the increased efficiency and low cost of cloud computing, which has greatly evolved since I conducted my analysis, I plan to include additional biases in my study in order to get a more complete insight into the constituents of skilled traders. Some of these biases will include, but are not limited to, overconfidence, conservatism, and information availability.

4.4 Future Work

I briefly conclude by discussing some future work that I aim to undertake. While my current dataset is limited in the variables related to demographics I aim to

obtain a more up to date dataset which includes demographic features such as gender, age, location among other variables. This would allow me to control for the impact of these demographic features on heterogeneity and performance.

Another aspect of foreign exchange trading that I want to investigate is the longevity of trader accounts. Trader accounts can have very short lifetime in the context of short-term trading in the foreign exchange market given the high leverage ratios offered by brokers which can be detrimental to their wealth. Examining how quickly a trader ceases trading activity and/or replenishes his account will provide a more complete picture of the performance of retail FX traders.

Thirdly I aim to investigate the impact of volatility and behavioural biases on skill at the institutional level. To my knowledge there are no studies which investigate this area, thus I intend to conduct this analysis in order to compare and highlight potential differences between the behaviour of institutional traders compared to individual traders in the foreign exchange market. I expect to find that institutional traders will exhibit fewer behavioural biases with a lesser magnitude compared to retail traders which will allow me to conduct a comparative analysis that underscores the impact of behaviour biases at the retail level. Moreover, I expect to find a higher level of skill among institutional traders which may be driven by information advantage, where institutional traders have access to more relevant information and better risk management techniques.

Another topic that I will investigate in the institutional level it is how order flow is distributed among the different liquidity providers and how a liquidity provider can optimise its inventory which has been discussed in the literature as the “hot potato

effect”. This means that liquidity providers can warehouse risk and optimise the holding time of trades in order to profit from the negative performance of some traders. I am already in talks with a multilateral trading facility (MTF) that has agreed to provide me this data which will make this study possible. Such an analysis would allow us to cluster traders into various groups based on risk and behavioural characteristics, which would grant brokers and liquidity providers detailed insight into their order flow. Consequently, they would be able to better manage their risks and hedge against profitable traders.

As FX trading continues to gain popularity and traction, it becomes more important to investigate the behaviour and characteristics of traders from a theoretical point of view, and understand the micro dynamics of FX markets and how trading decisions are made.

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Tables

Table 1.1: Descriptive Statistics of Traders on the Anonymous Platform.

The following table shows the descriptive statistics of traders on the Anonymous Platform. Several trading characteristics including Career SR, Career ROI, and Career BHA, account balance, trade duration, proportion of stop loss and take profit orders executed, percentage of long positions, volume, trade frequency, and account life are averaged first for each trader, and then across all traders.

Number of Trades	4,119,479										
Number of Traders	21,300										
Order Type											
<i>Manual</i>	68.32%										
<i>Stop Loss</i>	13.36%										
<i>Take Profit</i>	18.32%										
	Career SR	Career ROI	Career BHA	Balance	Duration (hours)	%SL	%TP	%Long	Volume	Trade Frequency	Account Life (Days)
<i>Mean</i>	0.60	-0.29	-0.09	1,806	24.3	18%	15%	46.10%	20,933	193	243
<i>Min</i>	0.00	-4.91	-1.00	0	1 (sec)	0%	0%	0%	667	1	0
<i>Max</i>	1.00	15.01	1.00	361,306	2,438.20	100%	100%	100%	7,611,111	87,354	918
<i>Standard Dev.</i>	0.22	0.52	0.31	8,825	68.15	23%	22%	19.87%	81,612	973	201

Table 1.2: Correlation Matrix of Variables.

The following table shows the correlations among the variables used in my analyses. These variables are the trading characteristics of traders on Anonymous and include Career SR and Career ROI, which are the average success rate and average return on investment of a trader over a specified period of time, respectively. Duration is the average trade duration of a trader. SL and TP are the proportions of trades for each trader that are triggered by a stop loss and take profit order, respectively. Long is the percentage of long trades executed by a trader. Volume is the average position size of a trader measured in USD. TradeFrequency is the number of trades executed by a trader.

	Career SR	Career ROI	Duration	SL	TP	Long	Volume	TradeFrequency
Career SR	1.00	0.12	0.06	-0.34	0.31	0.02	0.06	0.07
Career ROI	0.12	1.00	0.07	0.03	0.03	0.01	0.01	-0.04
Duration	0.06	0.07	1.00	-0.05	0.01	-0.03	-0.02	-0.02
SL	-0.34	0.03	-0.05	1.00	-0.18	-0.01	-0.03	-0.04
TP	0.31	0.03	0.01	-0.18	1.00	0.06	-0.01	0.03
Long	0.02	0.01	-0.03	-0.01	0.06	1.00	0.00	0.00
Volume	0.06	0.01	-0.02	-0.03	-0.01	0.00	1.00	0.33
TradeFrequency	0.07	-0.04	-0.02	-0.04	0.03	0.00	0.33	1.00

Table 2.1.1.1: Heterogeneity in Performance – Success Rate - Logistic Model Using Transaction Data.

This table shows the results of six models that regress the j^{th} trade success rate on the career success rate as well as other trading characteristics of traders over all previous trades. The control variables are the averages for each trader up to, but not including trade j , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)			(2b)			(2c)			(2d)			(2e)			(2f)		
	Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.	
Career SR	3.3892	0.0080	***	3.3848	0.0080	***	1.0889	0.0161	***	2.7852	0.02633	***	3.4236	0.0275201	***	4.6991	0.0115	***
Duration	2.50E-07	8.10E-09	***	2.40E-07	8.15E-09	***	6.65E-08	1.23E-08	***	2E-07	1.9E-08	***	2.4E-07	2.194E-08	***	1E-07	1E-08	***
SL	-0.3964	0.0071	***	-0.4084	0.0072	***	-0.4656	0.0183	***	-0.2793	0.02226	***	-0.19715	0.0218043	***	-0.0943	0.0092	***
TP	-0.0200	0.0057	***	-0.0371	0.0057	***	0.2614	0.0209	***	0.1979	0.02174	***	0.12332	0.0198761	***	-0.0596	0.0066	***
Long	-0.3628	0.0090	***	-0.3651	0.0090	***	-0.1781	0.0155	***	0.0417	0.02324	.	0.07611	0.0255362	**	-0.0884	0.0141	***
Volume	-0.0309	0.0016	***	-0.0300	0.0016	***	0.0026	0.0063		-0.0224	0.0073	**	-0.02199	0.0062013	***	-0.0255	0.0018	***
TradeFrequency	1.00E-05	4.21E-07	***	8.09E-06	4.41E-07	***	-0.0311	0.0019	***	-0.0013	0.00112		-0.0012	0.0006012	*	1E-05	5E-07	***
Intercept	-1.2900	0.007	***															
Sample		Full			Full		N <= 10			10 < N <= 25			25 < N <= 50			N> 51		
Year/Month FE		No			Yes		Yes			Yes			Yes			Yes		
Trader FE		No			Yes		Yes			Yes			Yes			Yes		
Pseudo R2		7.75%			7.78%		3.29%			6.36%			6.88%			9.87%		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2.1.1.2: Heterogeneity in Performance – Return on Investment - Logistic Model Using Transaction Data.

This table shows the results of six models that regress the j^{th} trade ROI on the career ROI as well as other trading characteristics of traders over all previous trades. The control variables are the averages for each trader up to, but not including trade j , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)		(2b)		(2c)		(2d)		(2e)		(2f)	
	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.
Career ROI	-6.06E-05	1.49E-03	-1.02E-04	1.49E-03	-8.25E-05	5.72E-03	-7.30E-05	2.20E-03	-1.48E-04	2.26E-03	3.00E-06	1.03E-04
Duration	2.95E+08	1.21E+08 *	3.07E+08	1.29E+08 *	1.14E+09	7.00E+08	5.65E+08	2.58E+08 *	3.80E+08	2.35E+08 ***	-7.78E+06	3.88E+06 ***
SL	-2.08E+13	2.04E+13	-2.08E+13	2.05E+13	-1.81E+14	1.04E+14	9.97E+13	4.05E+13 *	5.75E+13	3.70E+13 ***	-3.92E+12	6.39E+11 ***
TP	7.66E+12	2.33E+13	4.50E+12	2.34E+13	1.54E+14	1.23E+14	-2.51E+14	4.64E+13 ***	2.51E+13	4.17E+13 ***	8.29E+11	7.23E+11 ***
Long	2.54E+13	1.08E+13 *	2.67E+13	1.09E+13 *	6.41E+13	4.48E+13	4.13E+13	2.05E+13 *	-1.47E+13	2.06E+13 ***	-1.48E+11	4.01E+11 ***
Volume	2.26E+12	3.30E+12	2.45E+12	3.30E+12	8.99E+12	2.50E+13	7.99E+12	8.49E+12	5.14E+12	7.06E+12	6.04E+09	8.35E+10
TradeFrequency	2.89E+09	5.27E+09	2.44E+09	5.30E+09	4.13E+12	5.85E+12	2.68E+12	1.24E+12 *	3.77E+11	6.18E+11	-4.09E+07	1.19E+08
Intercept	-2.89E+13	9.19E+12 ***										
Sample	Full		Full		N <= 10		10 < N <= 25		25 < N <= 50		N > 51	
Year/Month FE	No		Yes		Yes		Yes		Yes		Yes	
Trader FE	No		Yes		Yes		Yes		Yes		Yes	
Pseudo R2	0.0001		0.0001		0.0001		0.0004		0.0001		0.0001	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2.1.2.1: Heterogeneity in Performance – Success Rate - Linear Model Using Daily Aggregated Data.

This table shows the results of six models that regress the t^{th} trading day success rate on the career success rate as well as other trading characteristics of traders over all previous trading days. The control variables are the averages for each trader up to, but not including day t , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)			(2b)			(2c)			(2d)			(2e)			(2f)		
	Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.	
Career SR	0.7042	0.0015	***	0.7016	0.0015	***	0.2531	0.0035	***	0.6244	0.0056	***	0.7433	0.0056	***	0.9282	0.0020	***
Duration	3.65E-08	1.40E-09	***	4.16E-08	1.46E-09	***	2.25E-08	2.83E-09	***	4.90E-08	3.99E-09	***	4.74E-08	4.40E-09	***	1.94E-08	2.28E-09	***
SL	-0.0884	0.0015	***	-0.0911	0.0015	***	-0.1196	0.0042	***	-0.0650	0.0050	***	-0.0465	0.0048	***	-0.0278	0.0018	***
TP	0.0013	0.0011		-0.0021	0.0011	.	0.0494	0.0043	***	0.0378	0.0045	***	0.0246	0.0041	***	-0.0008	0.0013	
Long	-0.0615	0.0017	***	-0.0613	0.0017	***	-0.0393	0.0034	***	0.0111	0.0050	*	0.0177	0.0053	***	-0.0070	0.0026	**
Volume	-0.0055	0.0003	***	-0.0054	0.0003	***	-0.0003	0.0013		-0.0040	0.0016	*	-0.0045	0.0013	***	-0.0039	0.0004	***
TradeFrequency	1.06E-06	7.98E-08	***	6.76E-07	8.47E-08	***	-0.0054	0.0004	***	9.27E-06	2.41E-04		-0.0001	0.0001		7.09E-07	8.49E-08	***
Intercept	2.36e-01	1.38e-03	***															
Sample		Full			Full			N <= 10			10 < N <= 25			25 < N <= 50			N > 50	
Year/Month FE		No			Yes			Yes			Yes			Yes			Yes	
Trader FE		No			Yes			Yes			Yes			Yes			Yes	
R2		9.64%			9.73%			4.52%			8.29%			8.78%			11.95%	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2.1.2.2: Heterogeneity in Performance – Return on Investment - Linear Model Using Daily Aggregated Data.

This table shows the results of six models that regress the t^{th} trading day ROI on the career ROI as well as other trading characteristics of traders over all previous trading days. The control variables are the averages for each trader up to, but not including day t , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)			(2b)			(2c)			(2d)			(2e)			(2f)	
	Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.
Career ROI	-1.42E-04	1.49E-03		-1.35E-04	1.39E-03		-1.00E-05	1.49E-03		-1.20E-05	1.48E-03		-1.25E-04	1.34E-03		-1.38E-04	1.34E-03
Duration	3.36E+08	1.38E+08	**	3.33E+08	1.33E+08	**	4.82E+05	1.38E+08		4.76E+05	1.38E+08		3.13E+08	1.24E+08	**	3.34E+08	1.32E+08
SL	-2.12E+13	2.05E+13		-2.22E+13	2.01E+13		-2.94E+13	2.05E+13		-2.49E+13	2.05E+13		-2.11E+13	2.02E+13		-2.52E+13	2.01E+13
TP	1.88E+12	2.35E+13		1.90E+12	2.34E+13		1.28E+12	2.35E+13		1.29E+12	2.54E+13		1.80E+12	2.64E+13		2.00E+12	2.34E+13
Long	2.77E+13	1.09E+13	**	2.37E+13	1.19E+13	**	1.01E+13	1.09E+13		1.22E+13	1.13E+13		2.53E+13	1.16E+13	**	2.57E+13	1.18E+13
Volume	2.51E+12	3.30E+12		2.21E+12	3.20E+12		1.91E+12	3.30E+12		1.91E+12	3.40E+12		2.11E+12	3.40E+12		2.20E+12	3.20E+12
TradeFrequency	-1.47E+10	2.80E+10		-1.46E+10	2.75E+10		-1.19E+10	2.80E+10		-1.19E+10	2.78E+10		-1.56E+10	2.75E+10		-1.46E+10	2.75E+10
Intercept	-2.84e+13	9.13e+12	***														
Sample	Full			Full			N <= 10			10 < N <= 25			25 < N <= 50			N > 50	
Year/Month FE	No			Yes			Yes			Yes			Yes			Yes	
Trader FE	No			Yes			Yes			Yes			Yes			Yes	
R2	2.20E-06			2.50E-06			1.40E-06			1.83E-06			1.90E-06			2.42E-06	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2.1.3.1: Heterogeneity in Performance – Success Rate - Logistic Model Using Daily Aggregated Data.

This table shows the results of six models that regress the t^{th} trading day dichotomized success rate on the career success rate as well as other trading characteristics of traders over all previous trading days. The control variables are the averages for each trader up to, but not including day t , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)		(2b)		(2c)		(2d)		(2e)		(2f)	
	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.
Career SR	1.0213	0.0187 ***	0.9938	0.0188 ***	0.1812	0.0263 ***	0.9298	0.0505 ***	1.4241	0.0606 ***	2.6751	0.0381 ***
Duration	5.61E-06	1.16E-07 ***	4.97E-06	1.21E-07 ***	4.34E-06	2.45E-07 ***	3.81E-06	3.18E-07 ***	3.54E-06	3.37E-07 ***	2.97E-06	1.85E-07 ***
SL	-0.6686	0.0179 ***	-0.7060	0.0180 ***	-0.3348	0.0354 ***	-0.5177	0.0463 ***	-0.6323	0.0487 ***	-0.6615	0.0274 ***
TP	0.4742	0.0202 ***	0.4452	0.0202 ***	0.3808	0.0424 ***	0.4186	0.0533 ***	0.5200	0.0553 ***	0.3583	0.0288 ***
Long	-0.0973	0.0095 ***	-0.0943	0.0096 ***	-0.1104	0.0152 ***	-0.0862	0.0237 ***	-0.0771	0.0270 **	0.0097	0.0172
Volume	-0.0139	0.0031 ***	-0.0146	0.0031 ***	0.0220	0.0083 **	-0.0098	0.0092	-0.0249	0.0109 *	0.0068	0.0038 .
TradeFrequency	4.98E-05	4.07E-06 ***	5.27E-05	4.12E-06 ***	-0.0028	0.0020	-0.0010	0.0014	-0.0019	0.0008 *	4.08E-05	4.29E-06 ***
Intercept	-4.44e-01	1.42e-02 ***										
Sample	Full		Full		N <= 10		10 < N <= 25		25 < N <= 50		N > 51	
Year/Month FE	No		Yes		Yes		Yes		Yes		Yes	
Trader FE	No		Yes		Yes		Yes		Yes		Yes	
Pseudo R2	1.10%		1.26%		0.84%		1.00%		1.34%		1.90%	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2.1.3.2: Heterogeneity in Performance – Return on Investment - Logistic Model Using Daily Aggregated Data.

This table shows the results of six models that regress the t^{th} trading day dichotomized ROI on the career ROI as well as other trading characteristics of traders over all previous trading days. The control variables are the averages for each trader up to, but not including day t , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)		(2b)		(2c)		(2d)		(2e)		(2f)	
	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.
Career ROI	6.33E-19	1.30E-18	8.46E-19	1.31E-18	1.28E-18	1.45E-18	-1.09E-17	4.11E-18 ***	1.19E-17	7.30E-18	6.70E-17	1.81E-17 ***
Duration	-3.52E-06	1.16E-07 ***	-3.45E-06	1.21E-07 ***	-6.29E-07	2.66E-07 **	-3.00E-06	2.85E-07 ***	-3.86E-06	2.92E-07 ***	-5.56E-06	2.21E-07 ***
SL	-1.51E-01	1.77E-02 ***	-1.62E-01	1.78E-02 ***	-1.10E-01	2.75E-02 ***	-2.26E-01	3.86E-02 ***	-1.80E-01	4.46E-02 ***	-2.28E-01	4.08E-02 ***
TP	3.75E-01	2.02E-02 ***	3.85E-01	2.04E-02 ***	3.10E-01	2.97E-02 ***	5.39E-01	4.42E-02 ***	4.63E-01	5.30E-02 ***	3.88E-01	5.03E-02 ***
Long	-1.11E-01	9.49E-03 ***	-1.14E-01	9.54E-03 ***	-1.21E-01	1.69E-02 ***	-1.55E-01	2.23E-02 ***	-9.36E-02	2.43E-02 ***	-8.31E-02	1.68E-02 ***
Volume	3.66E-03	2.86E-03	5.27E-03	2.86E-03 *	-3.46E-03	6.99E-03	1.66E-02	7.47E-03 **	3.28E-03	6.56E-03	-5.88E-05	4.12E-03
TradeFrequency	-6.42E-06	2.37E-05	-1.03E-04	2.46E-05 ***	2.36E-03	1.86E-03	-2.25E-03	1.19E-03 *	-1.40E-03	6.88E-04 **	-1.03E-04	3.14E-05 ***
Intercept	-9.94E-02	8.00E-03 ***										
Sample	Full		Full		N <= 10		10 < N <= 25		25 < N <= 50		N > 51	
Year/Month FE	No		Yes		Yes		Yes		Yes		Yes	
Trader FE	No		Yes		Yes		Yes		Yes		Yes	
Pseudo R2	0.18%		0.34%		0.30%		0.34%		0.31%		0.42%	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2.2: Heterogeneity in Expectations.

This table shows the results of Equations 2.3 and 2.4 on the full sample of traders, as well as on a restricted sample of traders with more than 30 trades. The table shows the number of traders that are identified as having an *Individual* effect, an *Idiosyncratic* effect, *Both* effects, or *Neither*, at the 95% and 99% significance levels.

	Full Sample				More than 30 Trades			
	Equation 2.3		Equation 2.4		Equation 2.3		Equation 2.4	
	95%	99%	95%	99%	95%	99%	95%	99%
<i>Significance Level</i>								
<i>Individual</i>	12,968	11,770	11,262	11,657	11,628	10,754	9,473	10,317
<i>Idiosyncratic</i>	-	-	1,264	829	-	-	1,130	778
<i>Both</i>	-	-	3,423	1,592	-	-	3,320	1,572
<i>Neither</i>	8,332	9,530	5,351	7,222	4,832	5,706	2,537	3,793
<i>Total</i>	21,300	21,300	21,300	21,300	16,460	16,460	16,460	16,460

Table 3.1: Impact of Volatility on Success Rate - Logistic Model Using Transaction Data.

This table shows the results of four models that regress the j^{th} trade success rate dummy on the market volatility of the EUR/USD as well as other trader characteristics that are computed as averages up to but not including trade j , which include, *Career SR*, the success rate of the trader up to trade j , *Duration*, the average duration of trades for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. *Volatility* is the daily standard deviation of spot price changes in Model (3.1.a), and it is a dummy variable that is equal to 1 if the standard deviation of spot prices on day $t-q$ is greater than the 70th, 80th, and 90th percentiles of standard deviations over the previous 30 trading days for Model (3.1.b), Model (3.1.c), and Model (3.1.d), respectively.

	Model (3.1.a)			Model (3.1.b)			Model (3.1.c)			Model (3.1.d)		
	Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.	
Career SR	3.3942	0.0080	***	3.3938	0.0080	***	3.3906	0.0080	***	3.3886	0.0080	***
Duration	2.47E-07	8.14E-09	***	2.53E-07	8.12E-09	***	2.54E-07	8.12E-09	***	2.53E-07	8.12E-09	***
SL	-0.3926	0.0071	***	-0.3951	0.0071	***	-0.3995	0.0071	***	-0.4011	0.0071	***
TP	-0.0262	0.0057	***	-0.0257	0.0057	***	-0.0251	0.0057	***	-0.0249	0.0057	***
Long	-0.3649	0.0090	***	-0.3631	0.0090	***	-0.3623	0.0090	***	-0.3604	0.0090	***
Volume	-0.0307	0.0016	***	-0.0306	0.0016	***	-0.0310	0.0016	***	-0.0311	0.0016	***
TradeFrequency	9.45E-06	4.25E-07	***	9.84E-06	4.24E-07	***	9.45E-06	4.22E-07	***	9.43E-06	4.22E-07	***
Volatility(t)	-102.0735	3.3836	***	-0.0604	0.0029	***	-0.0591	0.0030	***	-0.0975	0.0035	***
Volatility(t-1)	30.3273	3.3521	***	-0.0190	0.0032	***	-0.0343	0.0034	***	-0.0070	0.0040	.
Volatility(t-2)	20.3820	3.4634	***	0.0003	0.0036		0.0081	0.0040	*	-0.0236	0.0048	***
Volatility(t-3)	-14.4807	3.4111	***	-0.0215	0.0036	***	-0.0419	0.0041	***	-0.0412	0.0048	***
Volatility(t-4)	23.9693	2.6630	***	0.0396	0.0035	***	0.0178	0.0039	***	0.0007	0.0047	
Volatility(t-5)	19.8492	2.5801	***	0.0459	0.0032	***	0.0313	0.0036	***	0.0221	0.0044	***
Volatility(t-6)	18.4865	2.6671	***	-0.0031	0.0030		-0.0172	0.0032	***	-0.0211	0.0039	***
Volatility(t-7)	2.5257	3.6137		0.0093	0.0029	**	0.0010	0.0031		-0.0002	0.0037	
Volatility(t-8)	-33.5763	3.3934	***	-0.0220	0.0031	***	-0.0198	0.0033	***	-0.0110	0.0040	**
Volatility(t-9)	-0.8681	3.4839		0.0115	0.0036	**	-0.0107	0.0039	**	-0.0305	0.0047	***
Volatility(t-10)	3.5886	3.3968		0.0151	0.0035	***	0.0096	0.0039	*	-0.0096	0.0047	*
Year/Month FE	Yes			Yes			Yes			Yes		
Trader FE	Yes			Yes			Yes			Yes		
Pseudo R2	7.80%			7.79%			7.78%			6.37%		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.2: Impact of Volatility on Return on Investment - Logistic Model Using Transaction Data.

This table shows the results of four models that regress the t^{th} trading day ROI on the market volatility of the EUR/USD as well as other trader characteristics that are computed as averages up to day t , which include, *Career ROI*, the return on investment of the trader up to day t , *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. *Volatility* is the daily standard deviation of spot price changes in Model (3.2.a), and it is a dummy variable that is equal to 1 if the standard deviation of spot prices on day $t-q$ is greater than the 70th, 80th, and 90th percentiles of standard deviations over the previous 30 trading days for Model (3.2.b), Model (3.2.c), and Model (3.2.d), respectively.

	Model (3.2.a)			Model (3.2.b)			Model (3.2.c)			Model (3.2.d)		
	Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.	
Career ROI	-5.28E-05	1.49E-03		-5.18E-05	1.49E-03		-5.14E-05	1.49E-03		-5.86E-05	1.49E-03	
Duration	3.16E+08	1.35E+08	*	3.20E+08	1.34E+08	*	3.18E+08	1.33E+08	*	3.10E+08	1.33E+08	*
SL	-2.09E+13	2.04E+13		-2.13E+13	2.04E+13		-2.09E+13	2.04E+13		-2.12E+13	2.04E+13	
TP	8.19E+12	2.34E+13		7.55E+12	2.33E+13		7.58E+12	2.33E+13		7.45E+12	2.33E+13	
Long	2.57E+13	1.08E+13	*	2.56E+13	1.08E+13	*	2.55E+13	1.08E+13	*	2.57E+13	1.08E+13	*
Volume	2.38E+12	3.30E+12		2.37E+12	3.30E+12		2.37E+12	3.30E+12		2.36E+12	3.30E+12	
TradeFrequency	-8.33E+09	2.71E+10		-6.37E+09	2.70E+10		-6.51E+09	2.70E+10		-6.53E+09	2.70E+10	
Volatility(t)	-2.20E+15	6.10E+15		2.31E+12	5.47E+12		5.44E+10	6.04E+12		-4.68E+12	7.83E+12	
Volatility(t-1)	-2.49E+15	6.47E+15		4.54E+09	5.73E+12		-1.86E+12	6.35E+12		2.52E+12	8.33E+12	
Volatility(t-2)	1.58E+16	6.57E+15	*	9.44E+12	5.96E+12		1.16E+13	6.68E+12	.	1.12E+13	8.86E+12	
Volatility(t-3)	3.61E+15	6.22E+15		4.03E+12	5.90E+12		2.50E+12	6.60E+12		6.29E+12	8.66E+12	
Volatility(t-4)	-5.26E+15	4.97E+15		-1.33E+13	5.79E+12	*	-1.93E+13	6.43E+12	**	-6.32E+12	8.39E+12	
Volatility(t-5)	-1.79E+15	4.95E+15		5.65E+12	5.70E+12		1.60E+12	6.36E+12		2.02E+12	8.24E+12	
Volatility(t-6)	-1.16E+15	5.02E+15		1.58E+12	5.54E+12		6.58E+12	6.19E+12		3.18E+12	7.99E+12	
Volatility(t-7)	4.69E+15	6.14E+15		3.83E+12	5.52E+12		-2.20E+12	6.12E+12		5.15E+12	7.89E+12	
Volatility(t-8)	-2.14E+14	6.28E+15		2.02E+12	5.66E+12		4.73E+12	6.27E+12		-3.01E+12	8.15E+12	
Volatility(t-9)	3.02E+15	6.35E+15		5.92E+12	5.88E+12		5.52E+12	6.60E+12		7.48E+12	8.62E+12	
Volatility(t-10)	-2.10E+16	6.07E+15	***	-1.38E+13	5.80E+12	*	-2.09E+13	6.55E+12	**	-4.01E+13	8.57E+12	***
Year/Month FE	Yes			Yes			Yes			Yes		
Trader FE	Yes			Yes			Yes			Yes		
Pseudo R2	0.000035			0.000021			0.000028			0.000029		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.3: Impact of Volatility on Success Rate - Linear Model Using Daily Aggregated Data.

This table shows the results of four models that regress the t^{th} trading day success dummy on the market volatility of the EUR/USD as well as other trader characteristics that are computed as averages up to day t , which include, *Career SR*, the success rate of the trader up to day t , *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. *Volatility* is the daily standard deviation of spot price changes in Model (3.3.a), and it is a dummy variable that is equal to 1 if the standard deviation of spot prices on day $t-q$ is greater than the 70th, 80th, and 90th percentiles of standard deviations over the previous 30 trading days for Model (3.3.b), Model (3.3.c), and Model (3.3.d), respectively.

	Model (3.3.a)			Model (3.3.b)			Model (3.3.c)			Model (3.3.d)		
	Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.	
Career SR	0.705	0.002	***	0.705	0.002	***	0.704	0.002	***	0.703	0.002	***
Duration	3.62E-08	1.41E-09	***	3.71E-08	1.40E-09	***	3.72E-08	1.40E-09	***	3.66E-08	1.40E-09	***
SL	-0.088	0.001	***	-0.088	0.001	***	-0.089	0.001	***	-0.089	0.001	***
TP	4.16E-04	1.12E-03		0.001	0.001		0.001	0.001		0.001	0.001	
Long	-0.062	0.002	***	-0.061	0.002	***	-0.061	0.002	***	-0.061	0.002	***
Volume	-0.005	3.33E-04	***	-0.005	3.33E-04	***	-0.006	3.33E-04	***	-0.006	3.33E-04	***
TradeFrequency	9.22E-07	8.08E-08	***	1.00E-06	8.03E-08	***	9.57E-07	8.02E-08	***	9.71E-07	8.01E-08	***
Volatility(t)	-20.230	0.679	***	-0.010	0.001	***	-0.013	0.001	***	-0.019	0.001	***
Volatility(t-1)	5.988	0.665	***	-0.004	0.001	***	-0.008	0.001	***	-0.001	0.001	
Volatility(t-2)	3.984	0.686	***	0.001	0.001		0.002	0.001	*	-0.002	0.001	*
Volatility(t-3)	-2.816	0.679	***	-0.004	0.001	***	-0.006	0.001	***	-0.010	0.001	***
Volatility(t-4)	4.814	0.529	***	0.006	0.001	***	0.003	0.001	***	-0.003	0.001	**
Volatility(t-5)	3.955	0.512	***	0.008	0.001	***	0.007	0.001	***	0.003	0.001	**
Volatility(t-6)	3.588	0.530	***	0.001	0.001		-0.005	0.001	***	-0.007	0.001	***
Volatility(t-7)	0.742	0.718		7.16E-05	0.001		0.002	0.001	**	0.001	0.001	
Volatility(t-8)	-6.279	0.678	***	-0.004	0.001	***	-0.001	0.001	.	-0.012	0.001	***
Volatility(t-9)	-0.108	0.694		0.001	0.001	.	-0.002	0.001	**	-0.007	0.001	***
Volatility(t-10)	0.577	0.675		0.001	0.001	.	0.001	0.001		0.001	0.001	
Year/Month FE	Yes			Yes			Yes			Yes		
Trader FE	Yes			Yes			Yes			Yes		
R2	9.68%			9.67%			9.67%			9.67%		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Impact of Behavioural Biases on Skills

This table shows the results of regressing three performance measures, Success Ratio (SR), Return on Investment (ROI), and Big Hit Ability (BHA) on five behavioural indicators: herd initiations (HERD) is the correlation between the net open position of the trader and that of the dealer, disposition effect (DISP) is the proportion of gains realised minus the proportion of losses realised, sensation seeking (MU and MU2) where MU is the percentage of margin collateral that is used by the trader and MU2 is margin utilisation squared, inconsistent behaviour (INCON) is the standard deviation of the MU, and information advantage (INFO) is the average time it takes for a trade to cover the spread, as well as other control variables including average trade duration (Duration), account life (AccountLife), limit orders (SL and TP), position direction (Long), volume traded (Volume), and trade frequency (TradeFreq). Model (4.1) is a linear regression, which uses the continuous value of the performance measure, while Model (4.2) is a logistic model based on the dichotomized value of the performance measure. I also present the R2 and Pseudo R2 for the models.

	SR						ROI						BHA					
	Model (4.1)			Model (4.2)			Model (4.1)			Model (4.2)			Model (4.1)			Model (4.2)		
	Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.	
Intercept	0.572	0.004	***	0.508	0.051	***	-0.301	0.011	***	-1.186	0.052	***	-0.100	0.007	***	-0.976	0.048	***
Duration	4.44E-08	5.16E-09	***	2.58E-07	7.64E-08	***	1.37E-07	1.42E-08	***	7.69E-07	7.34E-08	***	6.24E-08	8.71E-09	***	4.03E-07	6.31E-08	***
AccountLife	4.30E-05	6.35E-06	***	5.54E-04	8.73E-05	***	-2.27E-04	1.75E-05	***	-1.30E-03	9.34E-05	***	-1.87E-05	1.07E-05	.	-6.12E-04	8.17E-05	***
SL	-0.240	0.006	***	-2.579	0.074	***	0.076	0.016	***	-0.606	0.083	***	-0.054	0.010	***	-0.450	0.074	***
TP	0.229	0.006	***	4.092	0.131	***	0.069	0.016	***	0.960	0.072	***	0.091	0.010	***	0.633	0.069	***
Long	0.001	0.006		-0.113	0.085		0.025	0.018		0.106	0.084		-0.002	0.011		0.008	0.079	
Volume	1.45E-10	3.93E-11	***	1.08E-08	2.21E-09	***	2.51E-10	1.08E-10	*	1.07E-10	5.71E-10		6.71E-11	6.63E-11		6.30E-10	4.84E-10	
TradeFreq	8.19E-06	1.37E-06	***	4.58E-04	7.75E-05	***	-2.46E-05	3.79E-06	***	-3.62E-04	5.90E-05	***	2.16E-07	2.32E-06		-6.66E-05	3.27E-05	*
HERD	1.26E-03	3.94E-05	***	9.88E-03	5.31E-04	***	3.60E-04	1.09E-04	***	6.74E-03	5.34E-04	***	4.59E-04	6.64E-05	***	3.53E-03	4.93E-04	***
DISP	0.213	0.005	***	1.373	0.064	***	-0.046	0.013	***	0.417	0.062	***	0.035	0.008	***	-0.068	0.058	
MU	0.006	0.001	***	-0.010	0.025		0.034	0.004	***	0.119	0.019	***	0.010	0.002	***	0.049	0.018	**
MU2	-8.32E-05	1.89E-05	***	-6.02E-04	2.65E-04	*	-5.52E-04	5.21E-05	***	-1.57E-03	2.73E-04	***	-1.36E-04	3.19E-05	***	-9.22E-04	2.32E-04	***
INCON	3.73E-07	1.48E-07	*	1.83E-05	3.45E-06	***	3.92E-06	4.08E-07	***	1.06E-05	2.22E-06	***	8.27E-07	2.50E-07	***	1.46E-05	2.28E-06	***
INFO	-2.63E-06	6.23E-07	***	-2.95E-05	1.40E-05	*	6.59E-07	1.72E-06		-2.47E-05	2.42E-05		4.99E-07	1.05E-06		-6.65E-05	4.24E-05	
R2 / Pseudo R2	29.82%			18.66%			3.35%			5.11%			1.74%			1.96%		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix

Table A.1: Heterogeneity in Performance – Success Rate - Logistic Model Using Transaction Data Including Career ROI.

This table shows the results of six models that regress the j^{th} trade success rate on the career success rate and career ROI, as well as other trading characteristics of traders over all previous trades. The control variables are the averages for each trader up to, but not including trade j , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)		(2b)		(2c)		(2d)		(2e)		(2f)	
	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.
Career SR	1.08E+00	2.07E-02 ***	1.05E+00	2.08E-02 ***	2.16E-01	2.95E-02 ***	1.02E+00	5.57E-02 ***	1.44E+00	6.65E-02 ***	2.66E+00	4.13E-02 ***
Career ROI	-7.43E-19	1.57E-18	-6.81E-19	1.57E-18	-8.05E-19	2.28E-18	-4.80E-18	3.49E-18	6.62E-18	4.09E-18	-2.42E-19	4.78E-18
Duration	-5.87E-06	1.28E-07 ***	-5.22E-06	1.33E-07 ***	-4.13E-06	2.80E-07 ***	-3.65E-06	3.53E-07 ***	-3.96E-06	3.74E-07 ***	-3.53E-06	2.00E-07 ***
SL	-6.79E-01	2.00E-02 ***	-7.14E-01	2.01E-02 ***	-3.17E-01	4.06E-02 ***	-5.17E-01	5.23E-02 ***	-6.49E-01	5.46E-02 ***	-6.70E-01	2.99E-02 ***
TP	4.79E-01	2.24E-02 ***	4.51E-01	2.24E-02 ***	4.25E-01	4.75E-02 ***	4.16E-01	5.93E-02 ***	5.20E-01	6.09E-02 ***	3.64E-01	3.19E-02 ***
Long	-9.51E-02	1.06E-02 ***	-9.39E-02	1.07E-02 ***	-1.32E-01	1.74E-02 ***	-8.82E-02	2.64E-02 ***	-5.52E-02	3.00E-02 *	3.42E-02	1.87E-02 *
Volume	1.68E-02	3.51E-03 ***	1.84E-02	3.52E-03 ***	3.69E-02	1.23E-02 ***	-6.98E-03	1.15E-02	2.36E-02	1.16E-02 **	1.04E-02	4.21E-03 **
TradeFrequency	5.56E-05	4.43E-06 ***	5.79E-05	4.50E-06 ***	-5.39E-03	2.28E-03 **	-1.33E-03	1.57E-03	-8.71E-04	8.89E-04	4.50E-05	4.69E-06 ***
Intercept	-4.66E-01	1.58E-02 ***										
Sample	Full		Full		N <= 10		10 < N <= 25		25 < N <= 50		N > 51	
Year/month FE	No		Yes		Yes		Yes		Yes		Yes	
Trader FE	No		Yes		Yes		Yes		Yes		Yes	
Pseudo R2	0.0119		0.0138		0.0095		0.0112		0.0145		0.0199	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.2: Heterogeneity in Performance – Return on Investment - Logistic Model Using Transaction Data Including Career Success.

This table shows the results of six models that regress the j^{th} trade ROI on the career ROI, career SR, as well as other trading characteristics of traders over all previous trades. The control variables are the averages for each trader up to, but not including trade j , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)			(2b)			(2c)			(2d)			(2e)			(2f)	
	Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.
Career SR	6.02E-02	5.98E-02		6.11E-02	5.85E-02		2.03E-02	7.57E-02		3.02E-02	6.74E-02		5.52E-02	6.01E-02		6.50E-02	5.30E-02
Career ROI	9.39E-20	3.83E-19		-3.45E-19	4.96E-19		-1.60E-18	8.97E-18		-2.58E-19	2.56E-18		7.08E-19	2.42E-18		-8.41E-18	7.84E-18
Duration	-7.30E-07	3.10E-08	***	-7.97E-07	7.23E-08	***	1.91E-06	1.64E-07	***	-1.70E-06	3.07E-07	***	-1.82E-06	3.61E-07	***	-2.06E-06	1.47E-07
SL	-2.63E-02	4.80E-03	***	1.63E-02	1.05E-02		1.55E-01	2.22E-02	***	-2.51E-02	5.07E-02		-1.32E-01	6.27E-02	**	-5.51E-02	2.26E-02
TP	8.29E-02	5.40E-03	***	5.81E-02	1.16E-02	***	5.28E-03	2.57E-02		7.86E-02	5.48E-02		1.56E-01	6.97E-02	**	1.10E-01	2.43E-02
Long	-2.25E-02	2.56E-03	***	-1.68E-02	4.82E-03	***	-2.30E-02	1.11E-02	**	-4.17E-02	2.01E-02	**	-2.82E-02	2.40E-02		-1.13E-02	1.01E-02
Volume	1.38E-03	8.37E-04		-9.06E-03	2.06E-03	***	-2.50E-02	1.45E-02	*	-2.55E-03	1.75E-02		8.53E-03	2.04E-02		-2.53E-03	2.87E-03
TradeFrequency	-5.40E-07	1.04E-06		-6.40E-06	2.11E-06	***	-4.62E-03	8.20E-04	***	-3.72E-03	5.43E-04	***	-1.88E-03	3.08E-04	***	-7.05E-06	2.24E-06
Intercept	4.31E-01	3.80E-03	***														
Sample	Full			Full			N <= 10			10 < N <= 25			25 < N <= 50			N> 51	
Year/Month FE	No			Yes			Yes			Yes			Yes			Yes	
Trader FE	No			Yes			Yes			Yes			Yes			Yes	
Pseudo R2	0.0030			0.0216			0.0477			0.0532			0.0490			0.0234	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.3: Heterogeneity in Performance – Success Rate - Logistic Model Using Transaction Data – 90% winsorisation.

This table shows the results of six models that regress the j^{th} trade success rate on the career success rate as well as other trading characteristics of traders over all previous trades. The control variables are the averages for each trader up to, but not including trade j , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)			(2b)			(2c)			(2d)			(2e)			(2f)		
	Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.	
Career SR	4.213	0.011	***	4.219	0.011	***	1.753	0.054	***	2.784	0.035	***	3.347	0.033	***	4.625	0.013	***
Duration	2.18E-07	1.03E-08	***	1.95E-07	1.03E-08	***	2.04E-07	2.49E-08	***	2.89E-07	2.61E-08	***	3.50E-07	3.00E-08	***	9.86E-08	1.40E-08	***
SL	-0.166	0.008	***	-0.173	0.008	***	-0.418	0.030	***	-0.309	0.025	***	-0.211	0.023	***	-0.095	0.009	***
TP	0.003	0.006		-0.016	0.006	***	0.258	0.030	***	0.175	0.023	***	0.115	0.020	***	-0.044	0.007	***
Long	-0.006	0.010		-0.010	0.010		0.000	0.027		0.066	0.025	***	0.086	0.027	***	-0.054	0.014	***
Volume	-0.022	0.002	***	-0.021	0.002	***	0.005	0.008		-0.022	0.008	***	-0.020	0.006	***	-0.022	0.002	***
TradeFrequency	9.93E-06	4.69E-07	***	7.06E-06	4.94E-07	***	-2.40E-03	3.45E-03		2.03E-03	1.20E-03	.	-2.00E-04	6.24E-04		8.01E-06	5.11E-07	***
Intercept	-2.07E+00	9.34E-03	***															
Sample	Full			Full			N <= 10			10 < N <= 25			25 < N <= 50			N > 51		
Year/Month FE	No			Yes			Yes			Yes			Yes			Yes		
Trader FE	No			Yes			Yes			Yes			Yes			Yes		
Pseudo R2	0.0694			0.0697			0.0172			0.0403			0.0488			0.0784		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.4: Heterogeneity in Performance – Return on Investment - Logistic Model Using Transaction Data – 90% winsorisation.

This table shows the results of six models that regress the j^{th} trade ROI on the career ROI as well as other trading characteristics of traders over all previous trades. The control variables are the averages for each trader up to, but not including trade j , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)		(2b)		(2c)		(2d)		(2e)		(2f)	
	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.
Career ROI	1.00E+13	2.31E+13	1.00E+13	2.41E+13	8.83E+13	1.73E+14	3.66E+13	5.21E+13	-4.26E+13	4.33E+13	-3.41E+11	3.21E+11
Duration	2.68E+08	1.35E+08 **	2.85E+08	1.43E+08 **	1.14E+09	7.53E+08	5.11E+08	2.81E+08 *	4.30E+08	2.63E+08	-7.38E+06	2.30E+06 ***
SL	-2.02E+13	2.27E+13	-2.01E+13	2.28E+13	-1.65E+14	1.11E+14	1.06E+14	4.42E+13 **	6.25E+13	4.11E+13	-6.79E+11	3.82E+11 *
TP	1.02E+13	2.59E+13	6.83E+12	2.60E+13	1.24E+14	1.32E+14	-2.42E+14	5.04E+13 ***	2.82E+13	4.64E+13	7.27E+11	4.27E+11 *
Long	2.94E+13	1.20E+13 **	3.09E+13	1.20E+13 **	7.15E+13	4.85E+13	5.11E+13	2.24E+13 **	-1.80E+13	2.30E+13	-1.12E+11	2.36E+11
Volume	2.12E+12	3.71E+12	2.30E+12	3.71E+12	9.40E+12	2.67E+13	6.90E+12	8.99E+12	5.29E+12	7.68E+12	-1.14E+09	5.04E+10
TradeFrequency	4.29E+09	5.72E+09	3.87E+09	5.76E+09	5.31E+12	6.35E+12	2.82E+12	1.35E+12 **	3.57E+11	6.88E+11	-7.18E+07	6.83E+07
Intercept	-2.75E+13	1.03E+13 ***										
Sample	Full		Full		N <= 10		10 < N <= 25		25 < N <= 50		N > 51	
Year/Month FE	No		Yes		Yes		Yes		Yes		Yes	
Trader FE	No		Yes		Yes		Yes		Yes		Yes	
Pseudo R2	0.0001		0.0000		0.0002		0.0008		-0.0001		0.0000	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.5: Heterogeneity in Performance – Success Rate - Linear Model Using Daily Aggregated Data – 90% winsorisation.

This table shows the results of six models that regress the t^{th} trading day success rate on the career success rate as well as other trading characteristics of traders over all previous trading days. The control variables are the averages for each trader up to, but not including day t , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)			(2b)			(2c)			(2d)			(2e)			(2f)	
	Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.
Career SR	2.1240	0.0320 ***		2.3142	0.0302 ***		1.645	1.94E-02 ***		2.0700	0.0247 ***		2.1390	0.0318 ***		2.3000	0.0318 ***
Duration	2.02E-06	1.09E-07 ***		1.68E-06	2.18E-07 ***		-2.63E-06	8.64E-07 ***		-1.79E-06	1.13E-06		-4.23E-06	1.40E-06 ***		2.75E-07	3.38E-07
SL	-0.0415	0.0016 ***		-0.0521	0.0054 ***		-0.0339	0.0220		-0.0867	0.0317 ***		-0.0020	0.0384		-0.0521	0.0083 ***
TP	0.0075	0.0012 ***		0.0334	0.0048 ***		0.0905	0.0232 ***		0.1949	0.0314 ***		0.2933	0.0376 ***		0.0056	0.0070
Long	0.0014	0.0021		0.0010	0.0038		-0.0281	0.0137 **		0.0243	0.0193		0.0188	0.0242		1.17E-02	6.12E-03 *
Volume	-0.0039	0.0003 ***		-8.57E-03	9.13E-04 ***		-0.0235	0.0108 **		-0.0257	0.0107 **		-3.38E-02	1.36E-02 **		-8.82E-03	1.07E-03 ***
TradeFrequency	9.47E-07	9.67E-08 ***		-2.09E-06	1.96E-07 ***		4.33E-03	6.94E-04 ***		-0.0032	0.0003 ***		-1.95E-03	1.45E-04 ***		-2.61E-06	0.000 ***
Intercept	8.28E-02	1.88E-03 ***															
Sample	Full			Full			N <= 10			10 < N <= 25			25 < N <= 50			N > 50	
Year/Month FE	No			Yes			Yes			Yes			Yes			Yes	
Traders FE	No			Yes			Yes			Yes			Yes			Yes	
R2	8.54%			10.44%			20.49%			16.51%			13.68%			11.19%	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.6: Heterogeneity in Performance – Return on Investment - Linear Model Using Daily Aggregated Data – 90% winsorisation.

This table shows the results of six models that regress the t^{th} trading day ROI on the career ROI as well as other trading characteristics of traders over all previous trading days. The control variables are the averages for each trader up to, but not including day t , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)		(2b)		(2c)		(2d)		(2e)		(2f)	
	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.
Career ROI	1.29E+13	2.31E+13	1.79E+13	2.43E+13	9.49E+13	1.44E+14	6.44E+12	2.37E+13	2.12E+13	1.59E+13	9.47E+08	8.31E+08
Duration	2.79E+08	1.48E+08 *	6.73E+08	2.36E+08 ***	1.84E+09	1.38E+09	-2.20E+08	2.95E+08	1.35E+06	2.13E+08	-2.33E+03	1.38E+04
SL	-2.10E+13	2.26E+13	2.89E+14	3.48E+13 ***	7.75E+14	1.44E+14 ***	-5.43E+13	3.99E+13	9.84E+12	3.10E+13	3.19E+08	2.35E+09
TP	1.01E+13	2.59E+13	5.94E+13	3.88E+13	1.08E+14	1.62E+14	2.89E+11	4.09E+13	2.87E+12	3.16E+13	2.47E+08	2.99E+09
Long	2.97E+13	1.20E+13 **	6.86E+12	1.60E+13	3.09E+13	8.82E+13	1.18E+13	2.18E+13	6.38E+12	1.62E+13	-2.10E+08	6.61E+08
Volume	2.24E+12	3.71E+12	3.26E+11	6.27E+12	2.11E+12	7.42E+13	-3.50E+11	1.33E+13	8.75E+10	5.36E+12	-9.78E+06	2.34E+08
TradeFrequency	-5.33E+09	2.93E+10	-8.52E+09	5.02E+10	-1.22E+12	5.38E+12	3.56E+11	4.22E+11	2.98E+10	1.62E+11	-1.13E+06	1.23E+06
Intercept	-2.67E+13	1.02E+13 ***										
Sample	Full		Full		N <= 10		10 < N <= 25		25 < N <= 50		N > 50	
Year/Month FE	No		Yes		Yes		Yes		Yes		Yes	
Traders FE	No		Yes		Yes		Yes		Yes		Yes	
R2	0.01%		0.01%		0.01%		0.01%		0.01%		0.01%	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.7: Heterogeneity in Performance – Success Rate - Logistic Model Using Daily Aggregated Data – 90% winsorisation.

This table shows the results of six models that regress the t^{th} trading day dichotomized success rate on the career success rate as well as other trading characteristics of traders over all previous trading days. The control variables are the averages for each trader up to, but not including day t , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)			(2b)			(2c)			(2d)			(2e)			(2f)		
	Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.	
Career Success	1.61E+00	3.16E-02	***	1.61E+00	3.18E-02	***	3.45E-02	7.94E-02		5.11E-01	8.12E-02	***	1.02E+00	8.21E-02	***	2.52E+00	4.43E-02	
Duration	-4.42E-06	1.35E-07	***	-3.87E-06	1.39E-07	***	-4.99E-06	3.57E-07	***	-4.06E-06	3.66E-07	***	-4.05E-06	3.65E-07	***	-3.05E-06	1.92E-07	
SL	-6.70E-01	2.09E-02	***	-7.04E-01	2.11E-02	***	-4.77E-01	5.63E-02	***	-5.43E-01	5.46E-02	***	-7.24E-01	5.38E-02	***	-6.87E-01	2.86E-02	
TP	5.11E-01	2.37E-02	***	4.76E-01	2.38E-02	***	4.13E-01	7.16E-02	***	4.41E-01	6.69E-02	***	6.09E-01	6.47E-02	***	4.23E-01	3.03E-02	
Long	-8.93E-02	1.07E-02	***	-8.34E-02	1.07E-02	***	-1.26E-01	1.97E-02	***	-1.17E-01	2.57E-02	***	-9.09E-02	2.83E-02	***	1.94E-03	1.75E-02	
Volume	6.07E-03	3.49E-03	.	7.19E-03	3.50E-03	**	6.96E-03	1.08E-02		-2.28E-02	1.15E-02	**	1.52E-02	1.31E-02		7.12E-03	4.12E-03	
TradeFrequency	4.89E-05	4.12E-06	***	5.09E-05	4.18E-06	***	-5.99E-03	2.54E-03	**	-4.80E-04	1.52E-03		-1.58E-03	8.32E-04	*	4.19E-05	4.33E-06	
Intercept	-8.02E-01	2.10E-02	***															
Sample	Full			Full			N <= 10			10 < N <= 25			25 < N <= 50			N > 51		
Year/Month FE	No			Yes			Yes			Yes			Yes			Yes		
Trader FE	No			Yes			Yes			Yes			Yes			Yes		
Pseudo R2	0.0089			0.0105			0.0046			0.0043			0.0074			0.0146		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.8: Heterogeneity in Performance – Return on Investment - Logistic Model Using Daily Aggregated Data – 90% winsorisation.

This table shows the results of six models that regress the t^{th} trading day dichotomized ROI on the career ROI as well as other trading characteristics of traders over all previous trading days. The control variables are the averages for each trader up to, but not including day t , and include *Duration*, the average duration of a trade for each trader, *SL* and *TP*, the proportion of trades that are triggered by stop losses and take profit orders, respectively, *Long*, the proportion of long positions, *Volume*, the average volume traded, and *TradeFrequency*, the number of trades executed by a trader. Model (2a) does not include time and trader fixed effects, while Model (2b) controls for both. Models (2c), (2d), (2e), and (2f) are conducted on subsamples that are selected according to the number of trades executed, which is a proxy for experience.

	(2a)			(2b)			(2c)			(2d)			(2e)			(2f)	
	Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.
Career ROI	2.38E-01	1.92E-02 ***		2.26E-01	1.92E-02 ***		5.72E-01	4.35E-02 ***		2.88E-01	4.58E-02 ***		1.19E-01	4.34E-02 ***		1.19E-01	2.92E-02 ***
Duration	-3.74E-06	1.22E-07 ***		-3.62E-06	1.27E-07 ***		-6.40E-07	2.79E-07 **		-3.24E-06	3.04E-07 ***		-3.65E-06	3.11E-07 ***		-5.76E-06	2.32E-07 ***
SL	-1.69E-01	1.87E-02 ***		-1.82E-01	1.89E-02 ***		-1.09E-01	2.87E-02 ***		-2.85E-01	4.13E-02 ***		-1.72E-01	4.81E-02 ***		-2.54E-01	4.32E-02 ***
TP	3.72E-01	2.13E-02 ***		3.78E-01	2.14E-02 ***		2.86E-01	3.12E-02 ***		5.12E-01	4.74E-02 ***		4.68E-01	5.65E-02 ***		3.99E-01	5.19E-02 ***
Long	-1.11E-01	9.97E-03 ***		-1.15E-01	1.00E-02 ***		-1.22E-01	1.76E-02 ***		-1.51E-01	2.38E-02 ***		-1.17E-01	2.57E-02 ***		-7.65E-02	1.75E-02 ***
Volume	7.14E-04	3.06E-03		2.86E-03	3.06E-03		-4.25E-03	7.28E-03		7.77E-03	8.17E-03		1.22E-03	7.39E-03		-1.31E-03	4.32E-03
TradeFrequency	2.37E-05	2.44E-05		-7.54E-05	2.53E-05 ***		1.15E-03	1.96E-03		-3.00E-03	1.27E-03 **		-1.46E-03	7.33E-04 **		-7.21E-05	3.23E-05 **
Intercept	-9.03E-02	8.48E-03 ***															
Sample	Full			Full			N <= 10			10 < N <= 25			25 < N <= 50			N > 51	
Year/Month FE	No			Yes			Yes			Yes			Yes			Yes	
Trader FE	No			Yes			Yes			Yes			Yes			Yes	
Pseudo R2	0.20%			0.37%			0.40%			0.38%			0.31%			0.44%	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$